EXHIBIT T

IN THE UNITED STATES DISTRICT COURT
FOR THE WESTERN DISTRICT OF NORTH CAROLINA
CHARLOTTE DIVISION

GEORGE MOORE and JAMES JILEK, **Plaintiffs,** **v.** **COMPASS GROUP USA, INC., D/B/A CANTEEN,** **Defendant.**	**No. 3:23-CV-818-RJC-DCK**

DECLARATION OF BRIAN KRIEGLER, PH.D.

Econ ONE Research, Inc.

March 6, 2024

Suite 800
550 South Hope Street
Los Angeles, California 90071

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LIST OF ATTACHMENTS

I, Brian Kriegler, declare as follows:

I. Introduction

1. I have personal knowledge of the facts set forth in this declaration, except where otherwise specified. If called to testify to these facts as a witness in this action, I would so testify.

2. I have been retained by the Plaintiffs in *George Moore, et al. v. Compass Group USA, d/b/a Canteen*, Case No. 3:23-CV-818-RJC-DCK, in the United States District Court for the Western District of North Carolina, Charlotte Division.

A. Qualifications and Fee Statement

3. I am a Managing Director at Econ One Research, Inc. ("Econ One"), an economic and statistical consulting firm with offices in Denver, Houston, Los Angeles, Memphis, New York, Sacramento, the San Francisco Bay Area, Washington, D.C, and India. I earned my M.S. and Ph.D. in statistics from UCLA and my B.A. in mathematics/economics from Claremont McKenna College. I have published several articles in peer-reviewed journals on the use of sampling and statistical modeling.

4. I have testified as an expert statistician in deposition and/or trial more than 80 times, collectively in the areas of wage and hour, civil rights, consumer protection, and breach of contract. I have been an invited speaker at numerous legal conferences, including the American Bar Association's Annual Labor and Employment Conference in 2017,[1] the California Employment Lawyers' Association Annual Conference in 2018,[2] the ABA's Fair Labor Standards Legislation mid-winter meeting in 2020,[3] and the Los Angeles County Bar Association's Labor and Employment

[1] "*Representative Evidence in Class Actions after Tyson Foods*." With Ryan Haggerty, John Ho, Rachhana Srey, and Debra Nahrstadt. 2017 Annual ABA Labor and Employment Law Conference, Washington, DC.

[2] "An Analysis of California Employment-Related Arbitrations," with Genie Harrison and Cliff Palefsky. 31st Annual CELA Conference, San Diego, CA.

[3] "Arbitrating Individual FLSA Claims Under Compulsion," with Matthew Helland, Sally Abrahamson, Eric Su, and Sheri Eisner. 2020 ABA FLSL Midwinter Meeting, Los Cabos, MX.

Symposium in 2023.[4] A true and correct copy of my curriculum vitae, which includes my testimonial experience, is attached hereto as **Attachment 1**.

5. Econ One currently is being compensated for the time I spend on this matter at $550 per hour. Econ One is being compensated for the time spent by other Econ One employees on this project at their normal and customary hourly rates.

B. Reports and Testimony in this Case to Date

6. To date, I have authored the following expert reports:

- Expert Report of Brian Kriegler, Ph.D., dated August 7, 2023 ("Kriegler Report") - A true and correct copy of the body of this report along with the appendix chapters on random sampling is attached hereto as **Attachment 2**.
- Supplemental Expert Report of Brian Kriegler, Ph.D., dated August 11, 2023 ("Kriegler Supplemental Report") - A true and correct copy of the body of this report is attached hereto as **Attachment 3**.[5]
- Second Supplemental Expert Report of Brian Kriegler, Ph.D., dated October 12, 2023 ("Kriegler Second Supplemental Report") - A true and correct copy of the body of this report is attached hereto as **Attachment 4**.

7. On August 23, 2023, I gave deposition testimony at opposing counsel's office in Los Angeles, California.

8. Except where specified otherwise, the terminology and methodology utilized in this declaration are the same as in the Kriegler Report.

[4] "Show Me the Money: Pay Transparency and Pay Equity Litigation," with Felicia Davis, Genie Harrison, and Ali Saad. 2023 LACBA Annual Labor & Employment Symposium, Los Angeles, CA.

[5] The Errata to the Supplemental Expert Report of Brian Kriegler, Ph.D. was dated August 25, 2023.

C. Assignment

9. The purpose of this declaration is to provide (i) a stratified random sample of machines located in Florida[6] ("Florida Stratified Random Sample"), and (ii) a stratified random sample of machines located in South Carolina[7] ("South Carolina Stratified Random Sample"). The methodology used to select each of these random samples is identical to the approach used to select the California Stratified Random Sample, as described in the Kriegler Supplemental Report.

II. Deriving / Defining the Sampled Populations

A. "Florida Stratum 1" and "South Carolina Stratum 1"

10. The "Florida Stratum 1" is the sub-population of all machines in Stratum 1 that were in Florida at or before the earliest survey date. There are 5,375 combinations of cost center and machine numbers that fit this description. Note that total Upcharges in Florida through the earliest survey date in this stratum are equal to $1,622,230.49.

11. Similarly, the "South Carolina Stratum 1" is the sub-population of all machines in Stratum 1 that were in South Carolina at or before the earliest survey date. There are 2,391 combinations of cost center and machine numbers that fit this description. Note that total Upcharges in South Carolina through the earliest survey date in this stratum are equal to $619,442.30.

B. "Florida Stratum 3" and "South Carolina Stratum 3"

12. "Florida Stratum 3" is the sub-population of all machines in Stratum 3 that were or are located in Florida. There are 1,169 combinations of cost center and machine numbers that fit this description. Note that total Upcharges in Florida are equal to $463,321.16.

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[6] Plaintiffs' counsel has advised me that the statute of limitation in Florida dates back to December 18, 2013. Given that the Two-Tier Revenue Report dates back to January 2014, it follows that all data pertaining to Florida in the Two-Tier Revenue Report was during said statute.

[7] Plaintiffs' counsel has advised me that the statute of limitation in South Carolina dates back to December 18, 2012. Given that the Two-Tier Revenue Report dates back to January 2014, it follows that all data pertaining to South Carolina in the Two-Tier Revenue Report was during said statute.

13. Similarly, "South Carolina Stratum 3" is the sub-population of all machines in Stratum 3 that were or are located in South Carolina. There are 55 combinations of cost center and machine numbers that fit this description. Note that total Upcharges in South Carolina are equal to $11,997.00.

III. Selecting Each State's Stratified Random Sample

14. All observations in Florida Stratum 1 are placed in a random order. Subsequently, the first 65 observations in this random order are selected. The same process and sample size is applied to South Carolina Stratum 1.

15. Similarly, all observations in Florida Stratum 3 are placed in a random order. Subsequently, the first 35 observations in this random order are selected. The same process and sample size is applied to South Carolina Stratum 3.

16. The Florida-specific stratified sample of 100 observations is shown in **Attachment 5A**. The South Carolina-specific stratified sample of 100 observations is shown in **Attachment 5B**. These exhibits are analogous to (i) Exhibit 2 in the Kriegler Report, and (ii) Supplemental Exhibit 1 in the Kriegler Supplemental Report. Within each stratum, the sampled observations are to be reviewed/analyzed in the order that they appear in this list.

IV. Potential Damages and Interest Calculations Pertaining to Florida and South Carolina

17. **Attachment 6** shows Upcharges for each unique combination of cost center and machine in the stratified random sample. **Attachment 6A** pertains to Florida, and **Attachment 6B** pertains to South Carolina. These exhibits are analogous to (i) Exhibit 4 in the Kriegler Report, and (ii) Supplemental Exhibit 2 in the Kriegler Supplemental Report.

18. **Attachment 7** shows potential pre-judgment interest for each unique combination of cost center and machine number in the stratified random sample. **Attachment 7A** pertains to Florida, and **Attachment 7B** pertains to South Carolina.[8] These exhibits

[8] Pre-judgment interest on Florida machines is calculated at 6 percent simple per annum, and pre-judgment interest on South Carolina machines is calculated at 9 percent simple per annum.. *See* Kriegler Report, Ex. 3.

are analogous to (i) Exhibit 5 in the Kriegler Report, and (ii) Supplemental Exhibit 3 in the Kriegler Supplemental Report. At the outset, pre-judgment interest is calculated through March 7, 2024.

19. **Declaration Table 1** below shows extrapolated potential principal damages and pre-judgment interest pertaining to the sampled population of machines in Florida, along with corresponding confidence intervals. This table is followed by **Declaration Table 2**, which pertains to South Carolina. These tables are analogous to Table 1 in the Kriegler Report, as well as Supplemental Table 1 in the Kriegler Supplemental Report.

Declaration Table 1:
Potential Principal Damages and Pre-Judgment Interest
Pertaining to Machines that Are or Were in Florida

Description	Using CLT-Based Formulas	Using Bootstrapping
Potential Principal Damages		
Extrapolated Total	$ 2,644,071	$ 2,647,425
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$ 2,090,772	$ 2,139,543
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$ 1,930,952	$ 2,004,359
Potential Pre-Judgment Interest		
Extrapolated Total	$ 814,357	$ 814,942
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$ 605,017	$ 619,199
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$ 544,540	$ 576,442

* - Equivalent to the lower bound of a two-sided 90 percent confidence interval

Declaration Table 2: Potential Principal Damages and Pre-Judgment Interest Pertaining to Machines that Are or Were in South Carolina		
Description	**Using CLT-Based Formulas**	**Using Bootstrapping**
Potential Principal Damages		
Extrapolated Total	$ 541,461	$ 541,144
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$ 426,423	$ 429,882
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$ 393,189	$ 401,130
Potential Pre-Judgment Interest		
Extrapolated Total	$ 285,126	$ 284,964
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$ 220,918	$ 223,744
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$ 202,369	$ 206,728
* - Equivalent to the lower bound of a two-sided 90 percent confidence interval		

V. Concluding Remarks

20. The same methodologies presented in both the Kriegler Report and in the Kriegler Supplemental Report are applied to the subset of machines that (i) are or were in Florida, and similarly, (ii) are or were in South Carolina.

21. Should additional, relevant information become available to me in this class action, I am open to incorporating it into my future calculations and opinions.

22. I declare the foregoing to be true under penalty of perjury of the laws of the State of North Carolina and the United States of America. Executed this 6th day of March, 2024.

Brian Kriegler, Ph.D.
March 6, 2024

ATTACHMENT 1

DR. BRIAN KRIEGLER
Managing Director
Los Angeles, California
Tel: 213 624 9600
Email: bkriegler@econone.com

Brian Kriegler is a Managing Director at Econ One Research in Los Angeles, California, bringing a wealth of expertise in sampling, statistics, and data analysis to his role. He is a distinguished expert statistician, testifying in both State and Federal courts in over 100 cases. The majority of these cases are wage and hour class/representative actions, and he also has testified in lawsuits involving discrimination, civil rights, consumer claims, and Medicare reimbursement.

Dr. Kriegler played a pivotal role in *Senne v. Major League Baseball*, a landmark class action lawsuit addressing systemic minimum wage and overtime violations among minor league baseball players. Retained by the plaintiffs, his classwide damages model involved "re-creating" the workday by combining player transactional data, team schedules, rosters, game information from the Minor League Baseball website, Google Maps, and survey data. Once the parties reached a settlement agreement, Dr. Kriegler was tasked with determining individual awards for each class member based on his analysis during the litigation.

Other noteworthy cases in which Courts have relied directly on Dr. Kriegler's analysis/opinions include:

- *Bennett v. Providence* - Employees alleged time rounding and missed meal periods
- Woodworth v. LLUMC - Employees alleged time rounding and missed meal/rest periods
- *Alberts v. Aurora* - Employees alleged missed meal/rest periods and off-the-clock work
- *Benton v. TNS* - Cell phone tower installers alleged underpaid overtime and missed meal/rest periods
- *Hamilton v. Walmart* - Fulfillment center employees alleged underpaid overtime and non-compliant meal periods
- *Espinoza v. East West Bank* - Plaintiff and the putative class alleged they were misclassified as salary exempt employees

Additionally, Dr. Kriegler and his team have built a versatile wage and hour consulting practice. These services include:

- *Damages analyses for mediation purposes* - Whether retained by the employer or employee(s), the primary aim of the Kriegler Group is to

assess the potential amount in unpaid wages and penalties should the event that the case proceeds to trial.

- *Historical and recurring time/pay audits for employers* - These evaluations are pivotal for monitoring the occurrence of deficient meal periods and daily overtime. Historical audits involve scrutinizing recent months or years of employer's data, while recurring audits entail developing a system capable of processing records on an ongoing basis.

- Review of employer's wage and hour policies and practices - Dr. Kriegler works directly with proactive business owners and operators to enhance labor operations, while at the same time assessing/mitigating the risk of significant legal disputes.

EDUCATION

Ph.D., Statistics, University of California, Los Angeles
M.S., Statistics, University of California, Los Angeles
B.A., Mathematics-Economics, Claremont McKenna College

WORK EXPERIENCE

Econ One Research, Inc.
Managing Director, January 2015 to Present
Statistician, August 2008 - December 2014

Claremont McKenna College (Silicon Valley Program), Guest Lecturer
Econ 123, Quantitative Data Analysis, March 2016
Econ 123, Quantitative Data Analysis, October 2015

University of Pennsylvania Department of Statistics, Post-Doctoral Researcher, 2007 - 2008

UCLA Department of Statistics, Lecturer
Statistics 10, Introduction to Statistical Reasoning, Winter 2008
Statistics 130B, Statistical Analysis with SAS, Summer 2007

Self-Employed, Statistical Consultant, 2004 - 2008

Claremont McKenna College Reed Institute for Applied Statistics, Post-Doctoral Researcher, 2007

RAND Corporation, Summer Associate, 2006

UCLA Department of Statistics, Graduate Student Researcher, 2004 - 2006

UCLA Department of Statistics, Technology Teaching Assistant Coordinator, 2004 - 2005

Lockheed Martin Missiles and Space, Associate Reliability Engineer, 2001 - 2003

INVITED PRESENTATIONS

"*Show Me the Money: Pay Transparency and Pay Equity Litigation*," with Felicia Davis, Genie Harrison, and Ali Saad. 2023 LACBA Annual Labor & Employment Symposium.

"*Using Experts in Wage and Hour Litigation Cases: Understanding Costs, Expectations, and the Role of Experts*," with Megan Lawson. 2022 Bridgeport Wage & Hour Litigation Conference, Los Angeles, CA.

"*Calculating Damages in Employment Cases*." 2022 Annual AAJ Convention, Seattle, WA.

"*Arbitrating Individual FLSA Claims Under Compulsion*," with Matthew Helland, Sally Abrahamson, Eric Su, and Sheri Eisner. 2020 ABA FLSL Midwinter Meeting, Los Cabos, MX.

"*An Analysis of California Employment-Related Arbitrations*," with Genie Harrison and Cliff Palefsky. 31st Annual CELA Conference, San Diego, CA.

"*Representative Evidence in Class Actions after Tyson Foods*," with Ryan Haggerty, John Ho, Rachhana Srey, and Debra Nahrstadt. 2017 Annual ABA Labor and Employment Law Conference, Washington, DC.

"*Effective Use of Statistical Evidence in Employment Class Action Litigation: Practical Guide in 2017*." Webinar presentation through The Knowledge Group with Eric Savage, Dubravka Tosic, Ph.D., and Paul White, Ph.D.

"*Counting the Homeless in Los Angeles County*." Joint Statistical Meetings, Seattle, WA, August 2006.

"*A Southpaw Secret: Are Their Salaries Consistent with Their Contributions to Team Performance*?" Claremont McKenna College, Claremont, CA, March 2002.

"*Mixing Component and System Data in Reliability Assessment*." United States Navy Complex, Washington, DC, July 2001.

PUBLISHED ARTICLES & PAPERS

"An Exploration and Validation of Confidence Intervals." Law360 (July 15, 2019).

"Practitioner's Guide to Stratified Random Sampling." Law360 (Nov 30-Dec 3, 2018).
Part 1: Four Reasons to Select a Stratified Random Sample
Part 2: Three Misconceptions About Stratified Random Sampling

"Practitioner's Guide to Statistical Sampling." Law360 (Jan 8-11, 2018).
Part 1: Validating Random Sampling and the Central Limit Theorem
Part 2: Resampling and Bootstrapping: A Method for Determining Confidence Intervals from Small Datasets
Part 3: Making Valid Statistical Inferences When Sample Selections Are Missing
Part 4: Three Myths About Random Sampling Requirements

"Delving Deeper into Duran." Law360 (Oct 1, 2014).

"Small Area Estimation of the Homeless Population in Los Angeles County: An Application of Cost-Sensitive Stochastic Gradient Boosting," Annals of Applied Statistics. Vol. 4 (3), 1234-1255, with Berk, R. (2010).

"Counting the Homeless in Los Angeles County." IMS Collections. Probability and Statistics: Essays in Honor of David A. Freedman, Vol. 2. 127-141, with Berk, R. and Ylvisaker, D. (2008).

"Cost-Sensitive Stochastic Gradient Boosting Within a Quantitative Regression Framework," Ph.D. Dissertation, Committee Chair: Richard Berk. Portions of this research have been implemented into the "gbm" library in R (open source statistical software) available at www.r-project.org (2007).

"Forecasting Dangerous Inmate Misconduct: An Application of Ensemble Statistical Procedures." Journal of Quantitative Criminology, 22(2). 131-145, with Berk, R. and Baek, J.H. (2006).

"Comparison of Achievement of 8th Graders Who Used the MathScape Curriculum to Those Who Used a More Traditional Curriculum," Creative Publications (2001).

"Estimation of Component and System Reliabilities Using Binomial and Exponential Data and Various Test Methods," Undergraduate Senior Thesis, Chair: Janet Myhre (2001).

REPRESENTATIVE CONSULTING ENGAGEMENTS

Employment

One-Time Compliance Audit

In the context of a pending class action, retained by a large restaurant chain to estimate how long various job activities took to complete. Worked with restaurant industry expert to develop a survey of kitchen managers.

Recurring Compliance Audits

Retained by a landscaping company to generate a monthly report on the extent of deficient meal periods and daily overtime. Each report included results by employee, by location, and across the State of California. Meal period compliance went from approximately 87 to 97 percent within a three-month period.

Retained by a San Diego-based restaurant chain with 12 locations to assist with meal period compliance and staffing optimization. Implemented a real-time software solution that reduced the rate of deficient meal periods by 45 percent.

Retained by a California restaurant chain with 20+ locations to assist in meal period compliance and to reduce unapproved daily overtime. Implemented a real-time software solution that helped the company save $20,000 annually in meal premiums and $35,000 annually in overtime pay.

Company Policies Audit

Retained by a manufacturing company to review company policies and time/pay practices. Made recommendations based on discussions with the employer and their management counsel.

False Claims Act

Medicare Reimbursements and Disgorgement

Retained by the relator, who alleged that a pharmaceutical company offered illegal kickbacks to doctors for prescribing specific drugs and inflated revenue for the pharmaceutical company. Constructed damages model that was used for settlement proceedings.

Medicare Audits

Regularly retained by a healthcare consulting firm to (i) select a random sample of Medicare claims, and (ii) perform extrapolations based on said sample once a medical expert has reviewed said sample. The results from sampling and extrapolation typically are submitted to the applicable Medicare Administrative Contractor (MAC).

Appellate Process

Retained to review/analyze the MAC's statistical sampling and overpayment extrapolation methods used to derive the amount that the Centers for Medicare/Medicaid Services demanded.

REPRESENTATIVE TESTIMONIAL ENGAGEMENTS

Employment

Time Rounding and Missed Breaks

Bennett v. Providence - To date, retained by the plaintiffs to calculate classwide damages stemming from time rounding and non-compliant second meal periods. Trial court granted summary adjudication on liability to the plaintiffs. Case is pending.

Missed Breaks and Off-the-Clock Work

Alberts v. Aurora - Retained by the plaintiffs to (i) analyze historical timekeeping and payroll records, along with survey data, and (ii) calculate classwide damages.

Missed Breaks and Underpaid Overtime

Benton v. Telecom Network Specialists - To date, retained by the plaintiffs to (i) analyze historical timekeeping and payroll records from numerous staffing companies, and (ii) calculate classwide damages. Case is pending.

DLSE v. Adat Shalom Board and Care - Retained by the defendant to evaluate the sampling design carried out by the DLSE.

Non-Compliant Breaks and Underpaid Overtime

Hamilton v. Walmart - Retained by the plaintiffs to analyze timekeeping data, payroll data, and security camera footage. Calculated damages and penalties stemming from various wage and hour violations.

Missed Breaks, Underpaid Overtime, and Off-the-Clock Work

Landon Fulmer v. Golden State Drilling - Retained by the plaintiffs to calculate classwide damages using class member deposition testimony, timekeeping, and payroll records.

Misclassification

Boyd v. Landsafe - Retained by the plaintiffs to calculate classwide damages using survey data, activity logs, and payroll records. Also worked with survey experts to design and implement a questionnaire to estimate hours worked.

Espinoza v. East West Bank - Retained by the defense to evaluate declarations and deposition testimony of potential class members prior to

class certification. Opined on Plaintiffs' experts' approach regarding the proposed use of surveying and sampling.

Seating

Lampkins v. Chase Bank - Retained by the plaintiff to analyze the length of time between transaction, the frequency of various types of transactions, and timekeeping data.

Discrimination

Capen v. Temecula Preparatory School - Retained by the plaintiff to conduct a statistical analysis of hiring and terminating practices at a charter school.

Horvath v. Western Refining - In a single plaintiff age discrimination case, conducted a statistical analysis of hiring and terminating practices at a logistics company.

Civil Rights

Over-Detention and Unlawful Strip Searches

Barnes v. District of Columbia - Retained by the plaintiffs to analyze inmate databases and to identify potentially impacted individuals. Also constructed a sampling design for selecting inmate files, and subsequently extrapolated the number of over-detentions and number of post-release strip-searched inmates based on a criminal justice expert's analysis of the sample.

Unlawful Strip Searches

Craft v. San Bernardino - Retained by the plaintiffs to analyze large databases to identify inmates who were subjected to strip searches (i) prior to their arraignment, (ii) after being ordered released, and/or (iii) in large groups. Collaborated with system administrators and officers from the law enforcement agency to construct criteria for identifying class members.

False Claims Act

Medicare Reimbursements

U.S. ex rel. Carlo Santa Ana v. Winter Park Urology - Retained by the relator, who alleged that the medical provider submitted improperly up-coded Medicare claims. Extrapolated damages based on a random sample of patients' data.

Antitrust

Large Transactional Data Analysis

Marchbanks v. Comdata - In a consulting role to the testifying expert to manage approximately one billion proprietary debit card transactions.

Collaborated with class administrator to locate class members and calculate damages for settlement purposes.

Consumer Class Actions/Breach of Contract

Unjust Enrichment

McAllister v. St. Louis Rams - Retained by the plaintiff, who alleged that season ticket holders were entitled to a refund for their personalized seating license. Developed a damages model and sampling methodology.

Moore v. Compass USA - Retained by the Plaintiffs, who alleged that they were not properly informed of higher fees when using a credit card at vending machines. Developed a sampling methodology and analyzed large transaction databases in order to calculate alleged classwide damages.

DR. BRIAN KRIEGLER
Prior Testimony/Reports

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
Employment						
1.	Richard Fairfield v. Advantage Rent-A-Car	Superior Court of the State of California, for the County of Los Angeles	BC342461	Declaration Declaration Declaration Deposition Supplemental Declaration	December 2006 February 2007 March 2007 March 2007 May 2007	Plaintiff
2.	Elveta Louise Francis v. State of California Department of Corrections	Superior Court of the State of California, for the County of Los Angeles	BC302856	Declaration Declaration	January 2007 May 2010	Plaintiff
3.	David Lubocki v. ZipRealty, Inc.	U.S. District Court, Central District of California	CV 07 2959 SJO (JCx)	Declaration	September 2007	Plaintiff
4.	Eric Moore v. Roadway Express, Inc. et al.	U.S. District Court, Central District of California	2:09-CV-01588 RBL (Opx)	Declaration	May 2010	Plaintiff
5.	Maria Martinez v. Jatco, Inc.	Superior Court of the State of California, for the County of Alameda	RG08397316	Deposition Trial	September 2011 December 2011	Defendant

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
6.	Valerie Alberts v. Aurora Behavioral Health Care	Superior Court of the State of California, for the County of Los Angeles	BC419340	Declaration Deposition Deposition Supplemental Declaration Declaration Deposition Reply Declaration Declaration Declaration Deposition Reply Declaration	May 2012 July 2012 October 2012 April 2013 December 2017 February 2018 April 2018 November 2020 May 2023 June 2023 August 2023	Plaintiff
7.	Patrick Santiago v. Amdocs, Inc.	U.S. District Court, Northern District of California	3:10-CV-04317 SI	Declaration Deposition	April 2013 May 2013	Plaintiff
8.	Christina Espinoza v. East West Bank	Superior Court of the State of California, for the County of Los Angeles	BC502166	Declaration Deposition	November 2014 February 2015	Defendant
9.	Crystal Brock v. Living Spaces Furniture; and Ronald Monroe v. Living Spaces Furniture	Superior Court of the State of California, for the County of Los Angeles	BC498415 / BC521299	Declaration	December 2014	Plaintiff
10.	Marie Minns, Kemberly Briggs v. Advanced Clinical Employment Staffing LLC, et al.	U.S. District Court, Northern District of California	3:13-03249-SI	Declaration Supplemental Declaration	February 2015 March 2015	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
11.	Kimberly Murphy v. CVS Caremark Corporation, et al.	Superior Court of the State of California, for the County of Los Angeles	BC464785	Declaration Deposition	March 2015 April 2015	Plaintiff
12.	Lorenzo Benton v. Telecom Network Specialists	Superior Court of the State of California, for the County of Los Angeles	BC354230	Declaration Deposition Declaration Supplemental Declaration Supplemental Declaration Supplemental Declaration Reply Declaration Declaration Deposition Trial Declaration	March 2015 May 2015 July 2017 November 2017 March 2018 April 2018 August 2018 August 2019 August 2019 January 2020 November 2020	Plaintiff
13.	Connie Capen v. Temecula Preparatory School, et al.	Superior Court of the State of California, for the County of Riverside	MCC 1300098	Declaration	April 2015	Plaintiff
14.	Terry P. Boyd v. LandSafe, et al.	U.S. District Court, Central District of California	SA13-CV-00561 DOC (JPRx)	Expert Report	July 2015	Plaintiff
15.	Valerie Horvath v. Western Refining Wholesale	Superior Court of the State of California, for the County of San Bernardino	CIVDS1311846	Declaration Deposition	November 2015 January 2016	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
16.	David Kaanaana v. Barrett Business Services, Inc., et al.	Superior Court of the State of California, for the County of Los Angeles	BC496090	Deposition Declaration Trial	December 2015 January 2016 February 2016	Plaintiff
17.	James Cole v. CRST, Inc.	U.S. District Court, Central District of California	EDCV 08-1570-VAP(SPx)	Declaration Deposition Expert Report Declaration	January 2016 February 2016 December 2016 February 2017	Plaintiff
18.	Christopher Williams v. Allstate Insurance Company	Superior Court of the State of California, for the County of Los Angeles	BC382577	Declaration	March 2016	Plaintiff
19.	Larry Loffredo v. Astro Spar, Inc.	Superior Court of the State of California, for the County of Los Angeles	BC559611	Declaration Deposition	March 2016 April 2016	Plaintiff
20.	Aaron Senne v. Office of the Commissioner of Baseball, et al.	U.S. District Court, Northern District of California	3:14-CV-00608-JCS / 3:14-CV-03289-JCS	Declaration Declaration Supplemental Declaration Expert Report Rebuttal Declaration Supplemental Expert Report Deposition Declaration Declaration Declaration	March 2016 April 2016 April 2016 August 2016 October 2016 August 2021 September 2021 November 2021 July 2022 January 2023	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
21.	Annette Blackwell v. Steve's Plating Corporation	Superior Court of the State of California, for the County of Los Angeles	BC531129	Deposition	March 2016	Defendant
22.	Bertha Sanchez v. St. Mary Medical Center	Superior Court of the State of California, for the County of San Bernardino	CIVDS 1304898	Declaration Deposition Rebuttal Declaration Rebuttal Declaration Deposition Declaration	April 2016 May 2016 July 2016 April 2018 April 2018 May 2018	Plaintiff
23.	Antoaneta Vatraleva v. Sears, Robuck & Co.	Superior Court of the State of California, for the County of Los Angeles	BC515650	Declaration	August 2016	Plaintiff
24.	Donald Harrington v. Marten Transport	U.S. District Court, Central District of California	15-CV-01419-MWF-ASx	Declaration	October 2016	Plaintiff
25.	Roderick Wright v. Renzenberger, Inc.	U.S. District Court, Central District of California	2:13-CV-06642-FMO-AGR	Expert Report	April 2017	Plaintiff
26.	Holly Attia v. The Neiman Marcus Group, Inc.	U.S. District Court, Central District of California	8:16-CV-00504 DOC (FFM)	Declaration	April 2017	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
27.	Clayton Dezan v. Dignity Health	Superior Court of the State of California, for the County of San Bernardino	CIVDS1516658	Declaration Deposition Rebuttal Declaration Declaration Declaration Reply Declaration Deposition Trial Trial	April 2017 June 2017 September 2017 August 2019 March 2021 July 2021 July 2021 August 2021 September 2021	Plaintiff
28.	Darel D. Woods v. JFK Memorial Hospital, Inc.	Superior Court of the State of California, for the County of Riverside	INC 1205209	Declaration Deposition Rebuttal Declaration Supplemental Declaration Declaration	May 2017 August 2017 December 2017 June 2018 August 2019	Plaintiff
29.	Isaac Rodriguez v. Nike Retail Services, Inc.	U.S. District Court, Northern District of California	5:14-CV-1508 BLF	Declaration Deposition Supplemental Declaration	June 2017 June 2017 August 2017	Plaintiff
30.	Eric Chavez v. Converse, Inc.	U.S. District Court, Northern District of California	15-CV-03746 NC	Declaration Expert Report Declaration Deposition Supplemental Declaration	June 2017 September 2017 September 2017 September 2017 September 2017	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
31.	Segundina Morin v. Physicians' Surgery Center of Downey, Inc.	Superior Court of the State of California, for the County of Los Angeles	BC625567	Deposition	July 2017	Plaintiff
32.	Amber Stewart v. Hat World, Inc.	Superior Court of the California, for the County of San Mateo	CIV 533617	Declaration Declaration Expert Report Supplemental Expert Report	August 2017 April 2018 January 2019 February 2019	Plaintiff
33.	Safeway Wage and Hour Cases	Superior Court of the State of California, for the County of Los Angeles	JCCP 4772	Rebuttal Declaration Deposition	August 2017 September 2017	Plaintiff
34.	Robyn James and Tiffany Belle v. American Corporate Security, Inc.	Superior Court of the State of California, for the County of Los Angeles	BC525388	Declaration	August 2017	Plaintiff
35.	Janae Brown v. Blazin' Wings, Inc	Superior Court of the State of California, for the County of Los Angeles	BC620185	Declaration Declaration Declaration	October 2017 July 2018 March 2019	Plaintiff
36.	Ta'quonna Lampkins et al. v. JP Morgan Chase Bank	U.S. District Court, Central District of California	11-CV-03428-PSG (PLAx)	Expert Report Supplemental Expert Report Expert Report Errata Supplemental Expert Report Errata Deposition	February 2018 March 2018 March 2018 March 2018	Plaintiff

Proceeding		Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
37.	Juan Garcia v. Walmart Stores, Inc.	U.S. District Court, Central District of California	5:16-CV-01645 TJH (RAOx)	Declaration Reply Declaration Expert Report Deposition Reply Expert Report	February 2018 May 2018 April 2019 April 2019 June 2019	Plaintiff
38.	Landon Fulmer, Jr. v. Golden State Drilling	Superior Court of the State of California, for the County of Kern	S-1500-CV-279707	Deposition	April 2018	Plaintiff
39.	Emmy Song v. THC-Orange County	U.S. District Court, Central District of California	8:17-cv-00965-JLS-DFMx	Declaration Deposition	April 2018 May 2018	Plaintiff
40.	Chelsea Hamilton v. Walmart Stores, Inc.	U.S. District Court, Central District of California	5:17-CV-01415	Declaration Deposition Reply Declaration Declaration Expert Report Supplemental Expert Report Supplemental Expert Report Deposition Trial	June 2018 July 2018 August 2018 September 2018 September 2018 November 2018 February 2019 March 2019 April 2019	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
41.	Nicole Woodworth v. Loma Linda University Medical Center	Superior Court of the State of California, for the County of San Bernardino	CIVDS1408640	Declaration Declaration Declaration Deposition Declaration Reply Declaration	June 2018 June 2018 December 2018 December 2018 February 2019 February 2019	Plaintiff
42.	Roderick Magadia v. Walmart Associates, Inc.	U.S. District Court, Northern District of California	17-CV-00062-LHK	Expert Report Deposition Supplemental Expert Report Trial	July 2018 September 2018 October 2018 December 2018	Plaintiff
43.	Christopher Wilson v. Harbor Rail Services	Superior Court of the State of California, for the County of Los Angeles	BC598348	Declaration	July 2018	Plaintiff
44.	Candice Ritenour v. Carrington Mortgage Services, LLC	U.S. District Court, Central District of California	8:16-CV-02011-CJC-DFM	Declaration	August 2018	Plaintiff
45.	Debbie Salazar v. See's Candy Shops, Inc	Superior Court of the State of California, for the County of Los Angeles	BC651132	Declaration Declaration	September 2018 December 2018	Plaintiff
46.	Janeice Thomas v. CheckSmart Financial, LLC	Superior Court of the State of California, for the County of Sacramento	34-2014-00168533-CU-OE-GDS	Declaration Declaration	October 2018 June 2019	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
47.	Maykel Rodriguez v. La-Z-Boy Inc	Superior Court of the State of California, for the County of San Bernardino	CIVDS1615392	Declaration	October 2018	Plaintiff
48.	Brandon Vawter v. United Parcel Service	U.S. District Court, Central District of California	2:18-cv-01318-RGK-E	Expert Report	November 2018	Plaintiff
49.	Gregorio Rosales et al. v. Professional Service Construction	Superior Court of the State of California, for the County of Orange	30-2016-00892554-CU-OE-CXC	Declaration	November 2018	Plaintiff
50.	Maria Herrera v. Federal Express Corporation	U.S. District Court, Central District of California	5:17-CV-02137	Declaration Deposition	November 2018 December 2018	Plaintiff
51.	Julio Garcia v. Walmart Associates, Inc.	U.S. District Court, Southern District of California	3:18-cv-00500-L-MDD	Declaration Declaration Expert Report Supplemental Expert Report Rebuttal Declaration	December 2018 December 2021 October 2022 October 2022 December 2022	Plaintiff
52.	Rose Gutierrez v. St. Bernardine Medical Center	Superior Court for the State of California, for the County of San Bernardino	CIVDS1703269	Declaration	February 2019	Plaintiff
53.	Sepehr Forghani v. Whole Foods Market California, Inc.	Superior Court of the State of California, for the County of Los Angeles	BC637964	Expert Report Deposition Amended Report Deposition	February 2019 February 2019 March 2019 April 2019	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
54.	Bryon Dittman v. Medical Solution, Inc.	U.S. District Court, Eastern District of California	2:17-CV-01851	Declaration	February 2019	Plaintiff
55.	Reginald Lyle v. Doctors Hospital of Manteca	Superior Court of the State of California, for the County of San Joaquin	STK-CV-UOE-2016-6523	Declaration Deposition	March 2019 April 2019	Plaintiff
56.	Division of Labor Standards Enforcement, Bureau of Field Enforcement v. Adat Shalom Board and Care	Department of Industrial Relations Office of the Labor Commissioner, State of California	35-CM-259095	Hearing	June 2019	Appellant
57.	Crystal Perkins v. Exclusive Wireless, Inc.	Superior Court of the State of California, for the County of Fresno	17CECG04108	Declaration	June 2019	Plaintiff
58.	Matthew Ogura v. Thrifty Payless, Inc.	Superior Court of the State of California, for the County of Los Angeles	BC605968	Declaration	June 2019	Plaintiff
59.	Cipriano Ponce v. Agro-Jal Farming Enterprises, Inc.	Superior Court of the State of California, for the County of San Luis Obispo	15 CV-0373	Declaration Reply Declaration	June 2019 September 2019	Plaintiff
60.	Salvador Ochoa v. CKE Restaurants Holdings; and Hermelinda Aguilar v. CKE Restaurants Holdings	Superior Court of the State of California, for the County of Los Angeles	BC623041 / BC686601	Declaration	July 2019	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
61.	Blanca Castaneda v. San Gabriel Transit	Superior Court of the State of California, for the County of Los Angeles	BC590907	Declaration	August 2019	Plaintiff
62.	Yelter Cruz v. Gelson's Market	Superior Court of the State of California, for the County of Los Angeles	BC670061	Declaration Deposition	August 2019 October 2019	Plaintiff
63.	Alyssa Diersing v. Sharp Rees-Stealy Medical Group	Superior Court of the State of California, for the County of San Diego--Central	37-2017-00029164-CU-OE-CTL	Declaration Deposition	September 2019 September 2019	Plaintiff
64.	Scott Carney v. Geo Drilling Fluids, Inc.	Superior Court of the State of California, for the County of Kern	BCV-15-101729	Declaration	September 2019	Defendant
65.	Stacy O'Braza v. Dignity Health	Superior Court of the State of California, for the County of Sacramento	34-2018-00240446	Declaration	October 2019	Plaintiff
66.	Michelle Flynn v. Macy's Corporate Services, Inc.	Superior Court of the State of California, for the County of Los Angeles	BC669170	Declaration	October 2019	Plaintiff
67.	Ser Lao v. H & M Hennes & Mauritz, L.P.	U.S. District Court, Northern District of California	5:16-CV-333 EJD	Expert Report Supplemental Expert Report Deposition	November 2019 November 2019 December 2019	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
68.	Jillian Hameister v. Jaco Oil Company	Superior Court of the State of California, for the County of Kern	BCV-17-102876	Declaration Reply Declaration	November 2019 May 2020	Plaintiff
69.	Juan Trevino v. Amazon Fulfillment Services, Inc.	U.S. District Court, Eastern District of California	1:18-cv-00120-DAD-BAM	Declaration Deposition Reply Declaration Declaration	November 2019 December 2019 January 2020 February 2020	Plaintiff
70.	Terrance Bailey v. Blue Apron, LLC	U.S. District Court, Northern District of California	3:18-CV-07000-VC	Declaration	December 2019	Plaintiff
71.	Armando Gutierrez Recendez v. ICO Builders, Inc.	Superior Court of the State of California, for the County of Los Angeles, Central District	BC720019	Deposition	December 2019	Defendant
72.	Rina Acosta v. Remington Hotels	Superior Court of the State of California, for the County of Contra Costa	MSC 16-02404	Declaration Declaration Declaration Declaration	December 2019 May 2021 September 2021 February 2023	Plaintiff
73.	Eric Camel v. Town of Chesterton	U.S. District Court, Northern District of Indiana, Hammond Division	2:19-CV-00065-JVB-JPK	Expert Report	January 2020	Plaintiff
74.	Keenan Patton v. Skyler Electric	Superior Court of the State of California, for the County of Nevada	CU17-082544	Declaration	January 2020	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
75.	Securitas Wage and Hour Cases	Superior Court of the State of California, for the County of Los Angeles	JCCP 4837	Declaration Declaration Deposition	January 2020 April 2020 May 2020	Plaintiff
76.	Ana Mandujano v. Macy's West Stores	Superior Court of the State of California, for the County of Los Angeles	19STCV33919	Declaration	January 2020	Plaintiff
77.	Rafael Balderrama v. Park West Landscape Maintenance, Inc.	Superior Court of the State of California, for the County of Los Angeles, Central District	BC 644491	Declaration Deposition	February 2020 January 2021	Plaintiff
78.	John Utne v. Home Depot U.S.A.	U.S. District Court, Northern District of California	3:16-CV-01854-RS	Rebuttal Declaration Deposition	March 2020 January 2022	Plaintiff
79.	Jesus A. Rios v. All Star Seed	Superior Court of the State of California, for the County of Imperial	ECU008770	Declaration	March 2020	Plaintiff
80.	Stephanie Heredia v. Eddie Bauer	U.S. District Court, Northern District of California	5:16-CV-06236-BLF (SVK)	Expert Report	March 2020	Plaintiff
81.	Juan Vincente De La Cruz v. Standard Drywall, Inc.	Superior Court of the State of California, for the County of Los Angeles	BC 591790	Declaration Deposition	March 2020 April 2020	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
82.	Saldana v. Amazon.com, LLC	U.S. District Court, Western Division of Kentucky at Louisville	3:14-MD-2504	Declaration	May 2020	Other*
83.	Robert Van Bebber v. Dignity Health	U.S. District Court, Eastern District of California	1:19-cv-00265-DAD-EPG	Declaration Declaration Deposition Reply Declaration Declaration Rebuttal Declaration Reply Declaration	September 2020 September 2020 October 2020 January 2021 March 2023 April 2023 May 2023	Plaintiff
84.	Melanie McCracken v. Riot Games, Inc.	Superior Court of the State of California, for the County of Los Angeles	18STCV03957	Declaration	November 2020	Plaintiff
85.	Felipe Villasenor v. Pizza Loca, Inc. Samuel Zarate v. La Pizza Loca, Inc.	Superior Court of the State of California, for the County of Los Angeles	BC642655 BC642714	Declaration Deposition	November 2020	Defendant
86.	Neutron Holdings Wage and Hour Cases	Superior Court of the State of California, for the County of San Francisco	CJC-19-005044	Declaration Declaration	December 2020 April 2021	Plaintiff
87.	Mauricio Navarro v. United Parcel Service, Inc.	Superior Court of the State of California, for the County of Los Angeles	BC592098	Declaration	December 2020	Plaintiff

* Retained by the plaintiff in Trevino v. Amazon Fulfillment Services to prepare a declaration in support of a motion to intervene.

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
88.	Kelvin Liu v. QNAP, Inc.	Superior Court of the State of California, for the County of Los Angeles	19PSCV00668	Declaration	January 2021	Plaintiff
89.	Jesenia Zamora and Brandan Griego v. Wal-Mart Stores, Inc.	U.S. District Court, Central District of California	3:20-CV-00401-BAS-AHG	Declaration Deposition	March 2021 April 2021	Plaintiff
90.	Casey Troyer v. The Yerba Mate Co., LLC	U.S. District Court, Northern District of California	3:20-CV-06065-WHA	Declaration	March 2021	Plaintiff
91.	Jose Delgado v. Taylor Farms California, Inc.	Superior Court of the State of California, for the County of Monterey	18-CV-001381	Declaration Deposition Trial Declaration Declaration Trial	April 2021 April 2021 May 2021 August 2021 August 2021 August 2021	Plaintiff
92.	Lynnett Myers v. Marietta Memorial Hospital	U.S. District Court, Southern District of Ohio, Eastern Division	2:15-CV-2956	Expert Report Rebuttal Expert Report Deposition	April 2021 May 2021 June 2021	Plaintiff
93.	Christine Crump v. Hyatt Corporation	U.S. District Court, Northern District of California	4:20-CV-00295-HSG	Declaration Deposition	May 2021 June 2021	Plaintiff
94.	Sharayah Bosch v. PeaceHealth	Superior Court of the State of Washington, for Clark County	20-2000924-06	Declaration	May 2021	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
95.	Keith Williams v. St. Joseph Personal Care Services	Superior Court of California, County of Orange	30-20-01134268-CU-OE-CXC	Declaration Deposition Reply Declaration	June 2021 September 2021 December 2021	Plaintiff
96.	Denver Davis v. Amazon Canada Fulfillment Services	Ontario Superior Court of Justice (Canada)	CV-20-00642361-00CP	Affidavit Reply Affidavit	July 2021	Plaintiff
97.	David Diaz v. Sun-Maid Growers of California	Superior Court of the State of California, for the County of Fresno	18CECG04501	Declaration Supplemental Declaration	August 2021 October 2022	Plaintiff
98.	Curtis Markson v. CRST International	U.S. District Court, Central District of California	5:17-CV-012610SB-(SPx)	Declaration Deposition	August 2021 June 2022	Plaintiff
99.	Benjamin Cardenas v. CVS Pharmacy	American Arbitration Association	01-19-0002-3726	Deposition Arbitration Hearing	September 2021 October 2021	Claimant
100.	George Stickles v. Atria Senior Living	U.S. District Court, Northern District of California	3:20-CV-09220-WHA	Declaration Deposition	October 2021 November 2021	Plaintiff
101.	In re Lowe's Companies, Inc. FLSA and Wage and Hour Litigation	U.S. District Court, Western District of North Carolina, Statesville Division	5:20-MD-2947-KDB-DSC	Expert Report Rebuttal Expert Report Deposition	October 2021 November 2021 December 2021	Plaintiff
102.	Josefina Martinez v. The Fairmont Miramar Hotel & Bungalows	Superior Court of California, for the County of Los Angeles	BC623651	Declaration	October 2021	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
103.	Tim Blackwell v. Climate Pros	U.S. District Court, Eastern District of California	2:20-CV-01968-KJM-CKD	Declaration Deposition	December 2021 January 2022	Plaintiff
104.	Clifford Feldman v. Aurora Las Encinas	Superior Court of the State of California, for the County of Los Angeles	20STCV24203	Deposition	January 2022	Plaintiff
105.	Ashley Thong and Idolina Valadez v. Outlook Resources	Superior Court of the State of California, for the County of Los Angeles	19STCV44400 20STCV43738	Declaration Reply Declaration	January 2022 June 2022	Plaintiff
106.	Luz Chinchilla v. C.G. Investments	Superior Court of the State of California, for the County of Los Angeles	BC665540	Declaration	January 2022	Plaintiff
107.	Paul Hancock v. Resource Enterprise Services	Superior Court of the State of California, for the County of Santa Clara	19CV358675	Declaration	January 2022	Plaintiff
108.	Charles Bates v. Leprino Foods	U.S. District Court, Eastern District of California	2:20-CV-00700-AWI-BAM	Declaration	February 2022	Plaintiff
109.	Lilia Ali v. Setton Pistachio of Terra Bella	U.S. District Court, Eastern District of California	1:19-CV-00959-JLT-BAM	Declaration Reply Declaration	February 2022 June 2022	Plaintiff
110.	Gerardo Soto v. Greif Packaging	Superior Court of California for the County of Orange, Civil Complex Center	30-2017-00952534-CU-OS-CXC	Declaration Deposition	April 2022 July 2022	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
111.	Brian Gile v. Dolgen California, LLC	U.S. District Court, Central District of California	5:20-CV-01863-MCS-SP	Declaration Deposition Reply Declaration Expert Report	May 2022 May 2022 June 2022 November 2022	Plaintiff
112.	Sara DeRosa v. ViacomCBS	U.S. District Court, Central District of California, Western Division	2:20-CV-02965-MCS (GJSx)	Declaration Deposition	June 2022 June 2022	Plaintiff
113.	Robert E. Owens, Jr. v. O'Reilly Automotive Stores, Inc.	Superior Court of California, County of Los Angeles	BC475210	Declaration Deposition	August 2022 November 2022	Plaintiff
114.	Robert Stafford, Jr. v. Bojangles' Restaurants, Inc.	U.S. District Court, Western District of North Carolina, Charlotte Division	3:20-CV-266-MOC	Expert Report Deposition Reply Expert Report	August 2022 October 2022 November 2022	Plaintiff
115.	John Perez v. Leprino Foods	U.S. District Court, Eastern District of California	1:17-CV-00686-AWI-BAM	Expert Report	August 2022	Plaintiff
116.	Frank Cuellar v. First Transit	U.S. District Court, Central District of California, Eastern Division	8:20-CV-01075-JWH-(JDEx)	Declaration	September 2022	Plaintiff
117.	Denise Droesch v. Wells Fargo Bank	U.S. District Court, Northern District of California	3:20-CV-06751-JSC	Declaration Deposition	October 2022 October 2022	Plaintiff
118.	Garrett Ramsey v. Geo Guidance Drilling Services	Superior Court of California, County of Kern	BCV-19-100463	Declaration Deposition	November 2022 January 2023	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
119.	Louis Ames and James Guiffrida v. San Antonio Regional Hospital	Superior Court of California, County of San Bernardino	CIVDS2018953	Declaration Deposition	November 2022 May 2023	Plaintiff
120.	Rosa Chavez and Estanislao Crisantos v. Crown Building Maintenance	Superior Court of California, for the County of Orange	30-2018-01040053-CU-OE-CXC	Declaration	January 2023	Plaintiff
121.	Esteban Palomino v. Northrop Grumman Systems Corporation	Superior Court of California, County of Santa Clara	19CV345534	Declaration Deposition Trial	January 2023 January 2023 January 2023	Plaintiff
122.	Fidel Torres, Henry Garcia, Francisco Muñoz, and Consuelo Alcala v. D/T Carson Enterprises	Superior Court of California, County of Riverside	RIC1821431	Declaration Deposition	January 2023 April 2023	Plaintiff
123.	David Hernandez v. Burdick Painting	Superior Court of California, County of Santa Clara	20CV363833	Declaration Deposition	January 2023 March 2023	Plaintiff
124.	Salvador Guzman and James Marshall v. Walmart	U.S. District Court, Northern District of California	21-CV-09133-NC	Declaration Deposition	February 2023 March 2023	Plaintiff
125.	Shailesh Jahagirdar v. CityMac	U.S. District Court, Western District of North Carolina, Asheville Division	1:20-CV-0033-MOC	Declaration Trial	February 2023 February 2023	Plaintiff*

* Under FRE 1006.

Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
126. Naomi Bennett and Janet Hughes v. Providence Health & Services	Superior Court of the State of Washington, for King County	21-2-13058-1 SEA	Declaration Declaration Expert Report Rebuttal Report Deposition	February 2023 September 2023 November 2023 January 2024 February 2024	Plaintiff
127. Claudia Carr and Lashawna Wicker v. Walmart	U.S. District Court, Central District of California	5:21-CV-01429-AB-KK	Declaration	February 2023	
128. Verna Maxwell Clarke v. AMN	U.S. District Court, for the Central District of California	2:16-CV-04132	Expert Report Supplemental Expert Report Deposition	March 2023 May 2023 June 2023	Plaintiff
129. Scott Williams v. U.S. Bancorp	Superior Court of California, County of San Francisco	CGC-10-499011	Declaration Deposition	April 2023 May 2023	Plaintiff
130. Yolanda Callister v. Swedish Health Services	Superior Court for the State of Washington, for King County	21-2-16148-7 SEA	Declaration	April 2023	Plaintiff
131. Arthur Ferrer v. Ameriflex	Superior Court of the State of California, County of Riverside	RIC2002157	Declaration	April 2023	Plaintiff
132. Andrew Howell v. Leprino Foods Company	U.S. District Court, Eastern District of California	1:18-CV-01404-AWI-BAM	Expert Report	April 2023	Plaintiff
133. Agustin Carmona Dionicio, Luis Melchor, and Mario Ramriez v. Pacific Agri-Products	Superior Court of California, County of Alameda	RG20070369	Declaration	May 2023	Defendant

Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
134. Ruben Porcayo v. So Cal Land Maintenance	Superior Court of the State of California, County of Orange	30-2021-01236054-CU-OE-CXC	Declaration Deposition	July 2023 September 2023	Plaintiff
135. Angel Vera v. Laurel Hardware	Superior Court of the State of California, County of Los Angeles -- Santa Monica	22SMCV00594	Deposition	August 2023	Defendant
136. Dwayne Lynch v. The Johns Hopkins Hospital	Circuit Court for Baltimore City, Maryland	24-C-23-000527	Declaration	August 2023	Plaintiff
137. Fernando Torres v. Johnston Nurseries	Superior Court of the State of California, for the County of Kern -- Metropolitan Division	BCV-19-100830-TSC	Declaration Deposition	September 2023 December 2023	Plaintiff
138. Anthony Cervantes and Mike Cross v. CRST	U.S. District Court, Northern District of Iowa -- Cedar Rapids Division	1:20-CV-00075-CJW-KEM	Expert Report Deposition Reply Report	November 2023 January 2024 January 2024	Plaintiff
139. Michael Bolden v. MobleWash	Superior Court of the State of California, County of Los Angeles	19STCV26304	Declaration	December 2023	Plaintiff
140. Dan Goldthorpe v. Cathay Pacific Airways	U.S. District Court, Northern District of California	3:17-CV-03233-VC	Declaration	January 2024	Plaintiff
141. Carson G. Taylor v. Seattle Children's Hospital	Superior Court of the State of Washington, for King County	22-2-15300-8 SEA	Declaration	January 2024	Plaintiff
142. LaMont Atkinson v. Life Care Centers of America	Superior Court of the State of Washington, for King County	22-2-00662-5 SEA	Declaration Declaration	January 2024 March 2024	Plaintiff

Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
143. Tammy Tenny v. Dignity Health	Superior Court of California, County of Kern	BCV-18-102316	Declaration Deposition Supplemental Declaration	February 2024 February 2024 February 2024	Plaintiff
Civil Rights					
144. Dianna Johnson v. U.S. Marshals	U.S. District Court, District of Columbia	02-2364 (RMC)	Declaration Declaration	July 2007 April 2010	Plaintiff
145. Marsial Lopez v. Sheriff Donny Youngblood	U.S. District Court, Eastern District of California	CV-F-07-0474 DLB	Declaration	June 2008	Plaintiff
146. Thomas Lee Goldstein v. City of Long Beach, John Henry Miller, William Collette, and Logan Wren	U.S. District Court, Central District of California	CV 04-9692 AHM (Ex)	Expert Report Deposition Declaration	November 2009 February 2010 June 2010	Plaintiff
147. Carl A. Barnes v. District of Columbia	U.S. District Court, District of Columbia	06-315 (RCL)	Declaration Expert Report Supplemental Expert Report Deposition Declaration Expert Report Declaration Expert Report Deposition Expert Report Trial	March 2010 November 2010 December 2010 December 2010 November 2011 February 2012 March 2012 June 2012 October 2012 November 2012 March 2013	Plaintiff

DR. BRIAN KRIEGLER
Prior Testimony/Reports

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
148.	Eric Jones v. Baltimore City Police Department, et al.	U.S. District Court, District of Maryland	CCB 05 CV 1287	Declaration Deposition Declaration	July 2010 October 2010 January 2011	Plaintiff
149.	Mary Amador v. Sheriff Leroy Baca, et al.	U.S. District Court, Central District of California	CV 10-1649 SVW (JEMx)	Declaration Declaration Declaration Declaration Declaration	October 2010 January 2011 June 2013 July 2013 February 2016	Plaintiff
150.	C. Alan Powell v. Jacqueline H. Barrett, et al.	U.S. District Court, Northern District of Georgia, Atlanta Division	1:04-CV-1100 (RWS)	Declaration	October 2011	Plaintiff
151.	Duncan Roy v. Sheriff Leroy Baca, et al.	U.S. District Court, Central District of California	CV 12-09012 BRO (FFMx)	Declaration Declaration Rebuttal Declaration Declaration Declaration Declaration	July 2014 May 2016 July 2016 May 2018 May 2018 November 2018	Plaintiff
152.	Marlon Johnson v. County of San Bernardino, et al.	U.S. District Court, Central District of California	5:18-CV-01121-GW (AFM)	Declaration	October 2019	Plaintiff
153.	William Scott Rogers v. Lewis & Clark County	Montana First Judicial District Court, Lewis and Clark County	DDV-2018-1332	Declaration	December 2022	Plaintiff

False Claims Act

Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
154. U.S. ex rel. Carlo Santa Ana v. Winter Park Urology Associates, P.A., et al.	U.S. District Court, Middle District of Florida	6:10-CV-806-28TBS	Expert Report Deposition	December 2012 February 2013	Plaintiff
155. U.S. ex rel. Misty Wall v. VistaCare Hospice Care, et al.	U.S. District Court, Northern District of Texas	3-07-CV-0604-M	Declaration Declaration Expert Report Rebuttal Report Deposition Declaration	August 2014 September 2014 July 2015 January 2016 January 2016 April 2016	Plaintiff
156. U.S. ex rel. Laura Lovett and Lisa Mayhew v. Holzer Clinic	U.S. District Court, Southern District of Ohio, Eastern Division	2:08-CV-312	Expert Report	March 2015	Plaintiff
157. Nicolle O'Neill v. Somnia	U.S. District Court, Eastern District of California	1:15-CV-00433-DAD-EPG	Expert Report	September 2021	Plaintiff
Breach of Contract/Unjust Enrichment					
158. In the Matter of City of Moss Point v. FEMA	U.S. Civilian Board of Contract Appeals	CBCA 2346-FEMA	Arbitration Hearing	June 2012	Plaintiff
159. Amtrust North America, Inc., v. SquareTrade, Inc.	Judicial Arbitration and Mediation Services, San Francisco Office	1100079447	Expert Report Supplemental Expert Report Declaration Arbitration Hearing Rebuttal Declaration	April 2015 May 2015 June 2015 June 2015 July 2015	Claimant

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
160.	Michael Nozzi v. Housing Authority of the City of Los Angeles, et al.	U.S. District Court, Central District of California	CV07-00380-PA (FFMx)	Declaration Expert Report Supplemental Expert Report Declaration	April 2016 February 2017 March 2017 March 2017	Plaintiff
161.	Ronald McAllister v. The St. Louis Rams, LLC	U.S. District Court, Eastern District of Missouri	4:16-CV-00172-SNLJ	Rebuttal Report Deposition	August 2017 September 2017	Plaintiff
162.	Amtrust North America, Inc. v. SquareTrade, Inc.	Judicial Arbitration and Mediation Services, San Francisco Office	1100086491	Expert Report	March 2018	Claimant
163.	Lisa Barkel-Williams v. Aoto Club Group and Auto Club Services	U.S. District Court, Eastern District of Michigan	2:19-CV-10403-DPH-MKM	Declaration Deposition	February 2024 February 2024	Plaintiff
Consumer/False Advertising						
164.	Christopher O'Shea v. Epson America, Inc., et al.	U.S. District Court, Central District of California	CV09-8063 PSG (CWx)	Declaration	February 2011	Plaintiff
165.	Manny Villanueva v. Fidelity National Title Company	Superior Court of the State of California, for the County of Santa Clara	1-10-CV-173356	Deposition Declaration Deposition Trial	March 2014 April 2014 April 2014 April 2014	Plaintiff
166.	Charlene Eike v. Allergan, Inc., et al.	U.S. District Court, East St. Louis Division	3:12-CV-01141-DRH-DGW	Expert Report Deposition	May 2014 August 2014	Plaintiff

	Proceeding	Court/Commission/Agency	Docket or File	Deposition/ Trial/Reports	Date	On Behalf Of
167.	Mohammed Rahman v. Mott's LLP	Superior Court of the State of California, for the County of San Francisco	CGC-13-532078	Declaration	October 2019	Plaintiff
168.	Carla Jimenez v. Charter Communications	Judicial Arbitration and Mediation Services, Irvine Office	1100106389	Arbitration Hearing	February 2023	Claimant
169.	George Moore v. Compass Group USA	United States District Court, Eastern District of Missouri, Eastern Division	4:18-CV-01962-SEP	Expert Report Supplemental Expert Report Deposition Supplemental Expert Report	August 2023 August 2023 August 2023 October 2023	Plaintiff
Miscellaneous						
170.	2009 Aircraft Tax Refund Cases: American Airlines, Inc. v. County of Los Angeles, et al, and United Airlines, Inc. v. County of Los Angeles	Superior Court of the State of California, for the County of Orange	JCCP 4803 / BC547243 / BC550656	Declaration	July 2017	Court Appointed

ATTACHMENT 2

IN THE UNITED STATES DISTRICT COURT
FOR THE EASTERN DISTRICT OF MISSOURI
EASTERN DIVISION

GEORGE MOORE, VIRGINIA CARTER, JAMES JILEK, FRANCIS JAYE, and SEAN MADELMAYER, **Plaintiffs,** **v.** **COMPASS GROUP USA, INC., D/B/A CANTEEN,** **Defendant.**	**No. 4:18-CV-01962-SEP**

EXPERT REPORT OF BRIAN KRIEGLER, PH.D.

Econ ONE Research, Inc.

August 7, 2023

Suite 800
550 South Hope Street
Los Angeles, California 90071

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LIST OF APPENDIX CHAPTERS AND EXHIBITS

Appendix Chapters

Exhibits

I. Introduction

1. I have personal knowledge of the facts set forth in this expert report, except where otherwise specified. If called to testify to these facts as a witness in this action, I would so testify.

2. I have been retained by the Plaintiffs in *George Moore, et al. v. Compass Group USA, d/b/a Canteen*, Case No. 4:18-CV-01962-SEP, in the United States District Court for the Eastern District of Missouri, Eastern Division.

3. Plaintiffs allege that Canteen had an extensive practice of failing to disclose to customers a price differential of $0.10 per transaction when making a purchase using a credit card, debit card, or pre-paid card. As a result, my understanding is that Plaintiffs and the putative class are seeking reimbursement for each of these alleged improper charges and pre-judgment interest.

A. Qualifications and Fee Statement

4. I am a Managing Director at Econ One Research, Inc. ("Econ One"), an economic and statistical consulting firm with offices in Denver, Houston, Los Angeles, Memphis, New York, Sacramento, the San Francisco Bay Area, Washington, D.C, and India. I earned my M.S. and Ph.D. in statistics from UCLA and my B.A. in mathematics/economics from Claremont McKenna College. I have published several articles in peer-reviewed journals on the use of sampling and statistical modeling.

5. I have testified as an expert statistician in deposition and/or trial more than 80 times, collectively in the areas of wage and hour, civil rights, consumer protection, and breach of contract. I have been an invited speaker at numerous legal conferences, including the American Bar Association's Annual Labor and Employment Conference in 2017,[1] the California Employment Lawyers' Association Annual Conference in 2018,[2] the ABA's Fair Labor Standards Legislation mid-winter meeting

[1] "*Representative Evidence in Class Actions after Tyson Foods*." With Ryan Haggerty, John Ho, Rachhana Srey, and Debra Nahrstadt. 2017 Annual ABA Labor and Employment Law Conference, Washington, DC.

[2] "An Analysis of California Employment-Related Arbitrations," with Genie Harrison and Cliff Palefsky. 31st Annual CELA Conference, San Diego, CA.

in 2020,[3] and the Los Angeles County Bar Association's Labor and Employment Symposium in 2023.[4] A true and correct copy of my curriculum vitae, which includes my testimonial experience, is attached hereto as **Exhibit 1**.

6. Econ One currently is being compensated for the time I spend on this matter at $520 per hour. Econ One is being compensated for the time spent by other Econ One employees on this project at their normal and customary hourly rates.

B. Assignment and Scope of this Expert Report

7. To date, my assignment is to provide a methodology for calculating classwide damages and pre-judgment interest, given my understanding of Plaintiffs' allegations and proposed class definitions. To do so, I propose the following three steps:

- Selecting a random sample of vending machines from a defined population;
- Obtaining and recording specific information about this sample of vending machines; and
- Using established statistical methods to extrapolate the results from the sample to the defined population.

8. This expert report includes seven sections, four appendix chapters, and two exhibits. Briefly:

a. Section II includes my understanding of Plaintiffs' allegations, the proposed class definitions, and the damages/interest that they seek. Section III provides a description of the data analyzed to date. Section IV covers a series of characteristics related to random sampling. In Section V, the stratified random sampling of vending machines is derived and defined. Section VI includes the methodology for calculating classwide damages and interest. Potential damages and pre-

[3] "Arbitrating Individual FLSA Claims Under Compulsion," with Matthew Helland, Sally Abrahamson, Eric Su, and Sheri Eisner. 2020 ABA FLSL Midwinter Meeting, Los Cabos, MX.

[4] "Show Me the Money: Pay Transparency and Pay Equity Litigation," with Felicia Davis, Genie Harrison, and Ali Saad. 2023 LACBA Annual Labor & Employment Symposium, Los Angeles, CA.

judgment interest are presented in Section VII. I offer concluding remarks in Section VIII.

b. The appendix chapters address various characteristics associated with random sampling.

c. The exhibits cover my curriculum vitae, the stratified random sample of vending machines, and potential damages/interest in said sample.

C. Materials Relied Upon

9. The materials relied upon to formulate my analyses and opinions in this expert report include the following:

Bates-stamped electronic data

- CG025 (Two-Tier Revenue Report)
- CG027 (Survey Instance Report)

Declarations and depositions

- Declaration of Martha Morgan, dated June 27, 2023
- Videoconference Deposition of Martha Morgan, Vol. III (June 28, 2023)
- Virtual Zoom Videotaped 30(b)(6) Deposition of Compass Group USA, Inc. by David Goldring, Vol. II (June 30, 2021)

Statistical textbooks and articles

- Berk, R.A. (2004) *Regression Analysis: A Constructive Critique*. Thousand Oaks: Sage Publications.
- Moore, D.S., and McCabe, G.P. (1999). *Introduction to the Practice of Statistics*. 3rd Ed. New York: W.H. Freeman.
- Moore, D.S., McCabe, G.P., and Craig, B.A. (2009). *Introduction to the Practice of Statistics*. 6th Ed. New York: W.H. Freeman.
- Thompson, Steven K. (2002). *Sampling*. 2nd Ed. New York: Wiley.

- *Reference Manual on Scientific Evidence* (2011). 3rd Ed. Federal Judicial Center. National Academies Press. Washington, DC.
- Efron, B. and Tibshirani, R.J. (1993). *An Introduction to the Bootstrap*. New York: Chapman & Hall.
- Statistical Sampling: A Toolkit for MFCUs. URL: https://oig.hhs.gov/fraud/medicaid-fraud-control-units-mfcu/files/MFCU%20Sampling%20Guidance%20Final.pdf.
- CMS Medicare Program Integrity Manual. URL: https://www.cms.gov/Regulations-and-Guidance/Guidance/Manuals/downloads/pim83c08.pdf.
- Dorfschmid, C. (December 2011). "Confidence and Precision in Claims Audits: Quality of the Estimate." URL: https://www.compliance.com/resources/confidence-and-precision-in-claims-audits-quality-of-the-estimate/.

D. Summary of Opinions

10. It is my opinion that the combination of Canteen's historical data, statistical sampling, and an eventual analysis of a stratified random sample of vending machines can be used to derive reliable estimates of classwide damages. Canteen's data is used to define a sampled population. Random sampling is applied in order to ensure that the selection of vending machines is neutral and unbiased. Total principal damages and pre-judgment interest will be extrapolated based on the results of the random sample of vending machines. Confidence intervals and margins of error of classwide totals will be calculated using established statistical methods.

11. In this instance, the review of a stratified random sample of vending machines is essential for two reasons.

- *First*, while Canteen conducted a survey of its vending machines in 2019-2020, Defendant's vice president of business information, Martha Morgan, indicated that the data that were recorded are subject to

human error.[5] By collecting, reviewing, and analyzing photographs of a random sample of previously-surveyed machines, this portion of classwide damages can be calculated and verified.

- *Second*, Canteen's survey did not cover all of its vending machines.[6] By collecting, reviewing, and analyzing additional information pertaining to a random sample of unsurveyed machines (*e.g.*, photographs), the portion of classwide damages pertaining to unsurveyed machines can be calculated and verified.

12. Data pertaining to the random sample is presented in a way to make it straightforward to update and utilize in the future. At the outset, the extrapolations herein are characterized as "potential" monetary awards because additional information about a stratified random sample is pending. Once the data on a random sample of vending machines have been collected, reviewed, and analyzed, the extrapolations will be updated using the methodologies described in Section VI herein.

II. Understanding of Plaintiff's Allegations and the Proposed Class Definitions

13. My understanding is that Canteen owns and operates over 200,000 vending machines in the United States. I further understand that many of these vending machines utilize a "two-tier" pricing structure for products sold in the machines. One tier is a cash price, and the other tier includes an upcharge of $0.10 when paying via credit card, debit card, or prepaid card ("Upcharge").[7]

14. I further understand that Canteen allegedly had an extensive practice of failing to disclose the $0.10 Upcharge. Therefore, Plaintiffs and the putative class are seeking damages for each transaction in which (i) the $0.10 Upcharge was not properly

[5] *See*, *e.g.*, Declaration of Martha Morgan, dated June 27, 2023 ("Morgan Decl."), ¶ 20.

[6] *See*, *e.g.*, Videoconference Deposition of Martha Morgan, Vol. III (June 28, 2023) ("Morgan Depo."), at 147:25-148:16.

[7] *See*, *e.g.*, Plaintiffs' Amended Consolidated Class Action Complaint, filed October 14, 2021 (Dkt. 126) ("Complaint"), ¶¶ 54-55.

disclosed on the machine, and (ii) the purchase was made via credit card, debit card, or prepaid card.[8]

15. My understanding is that the Plaintiffs seek certification of the following class:

> *Class*: All persons or entities who, within the applicable statute of limitations preceding the filing of this lawsuit to the date of class certification, purchased an item from a vending machine owned or operated by Defendant in the United States with a credit, debit or prepaid card and were charged an amount in excess of the price displayed for that item on the vending machine.

III. Data Description

A. Two-Tier Revenue Report

16. The "Two-Tier Revenue Report" (bates number CG025) includes information about each machine and the corresponding revenue. Noteworthy information in each row of data includes the following:

- The cost center identification number
- The machine number
- The physical address of the machine
- The date that the machine was surveyed (*i.e.*, examined by Canteen), if it was surveyed
- The amount of monthly revenue attributed to Upcharges

In total, the Two-Tier Revenue Report includes 309,485 rows of data with Upcharges spanning January 2014 to March 2023.

[8] *Id. See also*, Complaint, ¶¶ 66B, 75-77.

B. Survey Instance Report

17. The "Survey Instance Report" (bates number CG027) includes information about vending machines that purportedly have been examined internally by Canteen. Noteworthy information in each row of data includes the following:

- The cost center identification number
- The machine number
- The survey date (if applicable)
- Whether the vending machine has a "digital shopping cart" screen
- Whether the vending machine is a "cashless" device
- The machine model
- Whether the machine had a cash discount sticker at the time that the machine was surveyed
- A file directory and file name of an image purportedly showing the machine at the time that it was surveyed[9]

In total, the Survey Instance Report includes 246,943 rows of data.

IV. Overview of Random Sampling and Statistical Considerations

18. Random sampling is a process that generally involves three steps. *First*, a population of observations is defined. *Second*, a subset of observations is selected from the defined population. Each observation must have a known probability of selection. *Third*, statistical extrapolations, confidence intervals, and margin of error calculations are reported. These computations are a by-product of (i) the sampling design, (ii) the sample size, (iii) each observation's probability of selection, and (iv) the population size.

19. There are numerous advantages associated with relying on a random sample of observations from a defined population. *First*, random sampling provides formal and

[9] In CG027, the links to these file directories and file names are inactive and/or inaccessible.

scientific bases for calculating population estimates. *Second*, there are established methods for calculating reliable confidence intervals based on a random sample of observations. *Third*, random sampling inherently is neutral and unbiased.

20. The appendix chapters to this expert report cover various characteristics related to random sampling. In particular:

    a. **Appendix A** establishes that random sampling is a neutral and unbiased process. This appendix includes a discussion about the "Central Limit Theorem" ("CLT"). The CLT is a law in statistics that dictates when specific formulas can be used to calculate confidence intervals and the margin of error.

    b. **Appendix B** includes the derivation of several formulas pertaining to the margin of error and confidence intervals when the sample is "large enough" to invoke the CLT.

    c. **Appendix C** provides an alternative approach for deriving confidence intervals and the margin of error that do not depend on the CLT. This is especially valuable if conditions for the CLT have not been met, *e.g.*, if the number of sampled observations is relatively small.

    d. **Appendix D** includes proof that confidence intervals are likely to be within 5 percent of the stated level of confidence for random sample sizes of at least 25 observations.[10]

21. The next two subsections collectively address (i) the calculation of confidence intervals and margins of error, and (ii) a common misperception about the relationship between the population size and sample size.

A. Confidence Interval and the Margin of Error Considerations

22. Deciding what confidence intervals to use and what margin of error to tolerate depends on the subject matter. There are no universal statistical rules regarding what margin of error must be achieved, what level of confidence to use, or what type of

[10] For instance, using established methods/formulas for deriving a 90 percent confidence interval, the "true" amount of confidence is most likely at least 85 percent. Likewise, when deriving a 95 percent confidence interval, the "true" amount of confidence is most likely at least 90 percent.

confidence interval to use. These decisions are entirely about how much margin of error, *i.e.*, imprecision, the Court is willing to tolerate and what level of confidence the Court requires. Below I discuss each of these concepts in the context of this class action litigation and the discretion that I understand the Court has.

23. I understand that the Court has discretion regarding what margin of error is deemed tolerable when relying on a sample average to calculate damages. In general, the sample size must increase in order to achieve a smaller margin of error.

24. I further understand that the Court has discretion regarding what confidence interval to use. A 95 percent confidence interval is most common, but it is by no means a scientific standard. Numerous statistical textbooks discuss the use of other confidence levels, such as 90 percent.[11] In addition, the *Reference Manual on Scientific Evidence* discusses 68, 90, 95, and 99 percent intervals.[12] As the confidence level increases, the sample size must also increase in order to achieve a target margin of error. Conversely, lower confidence levels (*e.g.*, 80 or 90 percent) require smaller sample sizes in order to achieve a target margin of error.

25. My understanding is that the Court also has discretion in terms of whether it wants to rely on one-sided or two-sided confidence intervals. For instance, a two-sided 95 percent confidence interval may be 60 ± 10 percent. The interpretation is that with 95 percent certainty, the true percentage is between 50 and 70 percent. Alternatively, a one-sided confidence interval has a lower or upper bound, but not both. For example, suppose a one-sided 95 percent confidence interval produces an estimate of 60 - 10 percent. The correct interpretation is that, with 95 percent certainty, the true percentage is *at least* 50 percent. This lower bound of a one-sided 95 percent confidence interval is also the lower bound of a two-sided 90 percent confidence interval.

[11] *See*, *e.g.*, Moore, D.S., McCabe, G.P., and Craig, B.A. (2009). *Introduction to the Practice of Statistics*. 6th Ed. New York: W.H. Freeman. ("Moore *et al.*"), p. 364.

[12] *Reference Manual on Scientific Evidence* (2011). 3rd Ed. Federal Judicial Center. National Academies Press. Washington, DC. ("Reference Manual"), pp. 244-245.

26. It is important to note that a relatively high margin of error does not mean that a sample was not selected at random or that it is unreliable. Rather, *it highlights the importance of deriving, interpreting, and potentially applying the confidence interval.* The true population value falls within the confidence interval with a specified level of certainty. For instance, the trier of fact may choose to apply the lower bound of a confidence interval for determining classwide damages. This way, the trier of fact can be highly confident that classwide damages are not overestimated.[13]

27. When calculating damages, a one-sided confidence interval would appear to suit this Court's needs. As I understand it, Plaintiff has the burden to show the extent of liability and damages. It follows that the upper bound to a two-sided confidence interval is less essential. For example, suppose classwide damages are $10 million dollars with a margin of error of $1,000,000. This implies that we can be 95 percent confident that actual damages in the population are *at least* $9,000,000.[14] Thus, the lower bound signifies a conservative measure of classwide damages using established statistical principles.

28. The fact of the matter is that the desired level of confidence and target margin of error vary across professional industries and arenas. This is addressed in the statistical literature, industry standards, and court opinions. Consider the following textbooks and government agencies:

    a. In *Sampling*, author Steven K. Thompson characterizes 90, 95, and 99 percent confidence levels as "[t]ypical (arbitrary but conventional) choices."[15]

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[13] For example, suppose a random sample reveals 70 percent non-compliance, and that the margin of error is 15 percent. If this margin of error is based on a one-sided 95 confidence interval, then the true percentage is at least 55 percent with 95 percent confidence. If the confidence interval is two-sided, then the true percentage is between 55 and 85 percent with 95 percent confidence and at least 55 percent with 97.5 percent confidence. The Court could award damages based on the lower bound of one of these confidence intervals, the estimated average, or somewhere in between these two percentages.

[14] The lower bound of a one-sided 95 percent confidence interval is equivalent to the lower bound of a two-sided 90 percent confidence interval. In this hypothetical, we can be 90 percent certain that damages are between $900,000 and $1.1 million.

[15] Thompson, Steven K. (2002). *Sampling.* 2nd Ed. New York: Wiley ("Thompson"), p. 29.

b. In the *Introduction to the Practice of Statistics*, David S. Moore *et al.* explain that "[f]or most problems you would choose a confidence level of 90%, 95%, or 99%."[16]

c. The CMS Medicare Program Integrity Manual states that "[i]n most situations the lower limit of a **one-sided 90 percent confidence interval** shall be used as the amount of overpayment to be demanded for recovery from the provider or supplier. The details of the calculation of this lower limit involve subtracting some multiple of the estimated standard error from the point estimate, thus yielding a lower figure. This procedure, which, through confidence interval estimation, incorporates the uncertainty inherent in the sample…"[17]

d. The Office of Inspector General has published a guidebook on statistical sampling titled *Statistical Sampling: A Toolkit for MFCUs*. The stated thesis is "…to outline the basics of statistical sampling for use by State Medicaid Fraud Control Units (MFCUs) in calculating improper payment amounts." Therein it states "[m]ost agencies, as a matter of policy, use either a 90- or 95-percent confidence level. **A 90-percent confidence level is common in the Medicare administrative appeals process. A 95-percent confidence level is more common in academic settings.**"[18]

e. Strategic Management Services, LLC explains that the "OIG requires reporting the overpayment point estimate for the universe at 90% confidence level (two-sided) **and requires that it must reach a [margin of error] of +/- 25%**."[19]

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[16] Moore *et al.*, p. 363.

[17] https://www.cms.gov/Regulations-and-Guidance/Guidance/Manuals/downloads/pim83c08.pdf (bolded emphasis added)

[18] https://oig.hhs.gov/fraud/medicaid-fraud-control-units-mfcu/files/MFCU%20Sampling%20Guidance%20Final.pdf (bolded emphasis added)

[19] https://compliance.com/publications/confidence-and-precision-in-claims-audits-quality-of-the-estimate/ (bolded emphasis added)

To summarize, these textbooks and guidelines demonstrate that there are no hard, fast rules regarding the confidence levels and margins of error. The fact is that confidence intervals and margins of error are statistically reliable when the sample is selected at random and properly analyzed.

B. The Size of the Population Typically Does Not Drive the Sample Size

29. It is worth noting that a modest-sized random sample (*e.g.*, between 25 and 100 observations) can be used to draw valid statistical inferences about a relatively large population. In my experience, some practitioners claim that this cannot be done because (i) the population is so large relative to the sample size, and (ii) numerous variables must be controlled (*e.g.*, year, location) in order to draw valid statistical inferences. These perceptions are incorrect, for three established statistical reasons:

a. *First*, it is established in the statistical textbooks that the size of the population typically does not impact the number of observations in the sample.[20]

b. *Second*, it can be arithmetically proven that once the population is at least 10 times as large as the sample, the size of the population has virtually no impact on the margin of error for the average.[21]

c. *Third*, when the objective is to derive a confidence interval and margin of error for a singular population average, there is no statistical requirement to control for factors that vary across the defined population. By not controlling for certain data attributes in the sampling design, it may well be that the margin of error is relatively

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[20] *See*, *e.g.*, Moore *et al.*, p. 365 ("[t]he size of the population…does not influence the sample size"). *See also*, *Reference Manual*, p. 246 ("Population size (i.e., the number of items in the population) usually has little bearing on the precision of the estimates for the population average.").

[21] *See*, *e.g.*, Thompson, pp. 15, 40, 120. The author shows various formulas for the variance, which is equal to the square of the standard deviation. Part of this calculation entails deriving a "finite correction factor." The finite correction factor entails (i) taking the difference between the population and sample sizes, and (ii) dividing (i) by the population size. For instance, if the sample size is 100 and the population is 2,000, then this calculation equals 0.950. Thus, the finite correction factor will approach 1.0 if the sample is very small relative to the defined population size. All things being equal, the margin of error will decrease if the sample comprises a relatively large portion of the population.

higher. However, a relatively high margin of error does not signify that a confidence interval is statistically unreliable. *See* Appendix Chapter D herein.

V. Deriving / Defining the Sampled Population

30. In this instance, the sampled population is intended to include two groups of observations: (i) machines with a relatively high likelihood of having alleged invalid Upcharges, and (ii) machines that have not yet been surveyed. To the extent that Canteen has identified machines that, according to their records, do not have invalid Upcharges, they are carved out of the sampled population. Defining the sampled population entails five steps:

- *Step 1*: For each combination of cost center identification number (column C) and machine identification number (column D) in the Two-Tier Revenue Report, add together the Upcharges for a given month. For instance, suppose two rows of data have the same cost center and machine, and the Upcharges in January 2020 are $5 and $10. The newly created dataset will show include one row of data with this cost center and machine, and Upcharges in January 2020 of $15.

- *Step 2*: For each combination of cost center identification numbers (column P) and machine numbers (column AI) in the Survey Instance Report,[22] identify the row of data with the earliest survey date (column AF). Note that the day prior to the earliest survey date signifies the last day of potential damages.

- *Step 3*: Categorize the rows of data from Step 2 in which <u>all</u> of the following data conditions are met:

  - The status column (column B) is populated with "In Scope / Current" or "In Scope / Not Current."[23]

[22] *See* Morgan Depo., at 127:18-128:21.

[23] *See* Morgan Depo., at 153:4-155:21.

- The cashless device field (column W) is populated with a value of "Y"[24]
- The cash discount sticker field (column X) is populated with a value of "N"[25]
- The digital shopping cart field (column Y) shows a value of "N"[26]
- The machine model field (column AA) is not any one of the following "Machine Models Not at Issue:" (i) "Media Bev Max: 713 or 723," "Media Snack: 186 or 187," "Voce: 605, 606, or 607," or "Media Combo-Food: 471 or 472."[27]

These rows of data will be referred to as "Surveyed Machines - Category A." Conversely, rows of data pertaining to all other surveyed machines will be referred to as "Surveyed Machines - Category B."

- Step 4: Cross-reference the dataset in Step 3 with the dataset created in Step 1. Match records by cost center and by machine number.
- Step 5: From the cross-referenced dataset in Step 4, place each row of data into one of four strata:
  - *Stratum 1*: There are 50,293 combinations of cost center and machine number that are in both the Two-Tier Revenue Report and in "Surveyed Machines - Category A," for which Upcharges through the earliest survey date are greater than $0. Note that total Upcharges through the earliest survey date in Stratum 1 are equal to $12,051,294.75.
  - *Stratum 2*: There are 133,186 combinations of cost center and machine number that are in both the Two-Tier Revenue Report

[24] *See, e.g.*, Morgan Decl., ¶ 28e. *See also*, Morgan Depo., at 199:1-7.

[25] *See, e.g.*, Morgan Decl., ¶ 4.

[26] *See, e.g.*, Morgan Decl., ¶ 28a.

[27] *See* Virtual Zoom Videotaped 30(b)(6) Deposition of Compass Group USA, Inc. by David Goldring, Vol. II (June 30, 2021), Ex. 56 at slide 13. According to this document, the "Machine Models Not at Issue" included a digital shopping cart feature.

and in "Surveyed Machines - Category B," and where Upcharges from January 2014 through March 2023 are greater than $0.

- *Stratum 3*: There are 12,093 combinations of cost center and machine number in the Two-Tier Revenue Report and not in the Survey Instance Report, in which there are Upcharges greater than $0 in February 2023 and/or March 2023. Note that total Upcharges in Stratum 3 are equal to $2,376,499.

- *Stratum 4*: There are 58,704 combinations of cost center and machine number in the Two-Tier Revenue Report and not in the Survey Instance Report, in which Upcharges are $0 in February and March 2023.

31. Ultimately, a stratified random sample is selected (i) from Stratum 1, and separately, (ii) from Stratum 3. Subsequently, classwide principal damages are calculated by (i) extrapolating within Stratum 1, (ii) extrapolating within Stratum 3, and (iii) adding the results of Stratum 1 and Stratum 3 together.

32. Conversely, Stratum 2 and Stratum 4 are not sampled because Canteen's data suggest that (i) the machine did not generate allegedly invalid Upcharges, and/or (ii) the machine likely cannot be found. At the outset, no damages are calculated stemming from the observations in these two strata.

VI. Methodology for Extrapolating Classwide Principal Damages and Pre-Judgment Interest Using the Stratified Random Sample of Vending Machines

A. Determining the Sample Size and Selecting the Stratified Random Sample of Surveyed and Unsurveyed Observations

33. When utilizing random sampling, my general practice is twofold:

a. *Select the largest sample size allowed, given various pragmatic constraints.* All things being equal, this increases precision and reduces the margin of error. My experience is that the eventual sample size is a function of the amount of time that it takes to collect and review sampled records.

b. *Allow for the possibility that the sample size may be less than the anticipated maximum number.* One way to preserve the validity of statistical

inferences is to place sampled observations in a random order, and to have them reviewed/analyzed in the order that they appear. For example, suppose that the anticipated maximum sample size is 400 observations, but time constraints ultimately result in an analysis of 300 observations. Extrapolations will remain valid as long as the sampled observations are *the first* 300 that were selected.

34. In this instance, my understanding is that the sample data collection process involves (i) reviewing existing images of surveyed machines, (ii) examining and taking photos of unsurveyed machines,[28] and (iii) recording results based on the stratified random sample of machines. Accordingly, I anticipate that the sample size could be on the order of hundreds of observations.[29] Therefore, I have written computational programs to select at random 250 observations from Stratum 1 and 150 observations from Stratum 3. Specifically:

- All observations in Stratum 1 are placed in a random order. Subsequently, the first 250 observation in this random order are selected.
- All observations in Stratum 3 are placed in a random order. Subsequently, the first 150 observation in this random order are selected.

[28] Alternatively, my understanding is that Plaintiffs ultimately may request from Canteen specific pieces of information in writing about randomly sampled machines that have not been surveyed to date. Such information includes (i) whether the machine is a cashless device, (ii) whether the machine includes a digital shopping cart, and (iii) whether the machine already includes a label.

[29] It is worth noting that Canteen's vice president of business information, Martha Morgan, reviewed photographs of 120 machines. *See*, *e.g.*, Morgan Decl., ¶ 28, and Morgan Depo., at 190:24-7. The fact that Ms. Morgan characterized this review as a "spot check" suggests that it is feasible and practical to examine up to 250 photographs as recommended herein.

Relatedly, Ms. Morgan acknowledges that the list of 120 machines was provided to her by an attorney. *See* Morgan Depo., at 190:24-191:7. My understanding is that Canteen has not offered any documentation regarding the process that was used to select these 120 machines. Therefore at the outset, there is no statistical justification for projecting the results from these 120 machines onto any larger population.

35. The stratified sample of 400 observations is shown in **Exhibit 2**.[30] Within each stratum, the sampled observations are to be reviewed/analyzed in the order that they appear in this list.

1. Accounting for the Possibility of Missing and/or Incomplete Sampled Records

36. After a random sample has been selected/analyzed, one must be prepared for the possibility that some sampled observations will be missing and/or incomplete. Here, the issue comes to the forefront if information about some randomly sampled observations cannot be found.

37. While it is premature to know the prevalence of missing/incomplete records, below are methods that aid in preserving the ability to draw valid statistical inferences. I anticipate using one or more of these methods to the extent necessary.

a. *For observations in Stratum 1, assign the amount that currently appears in Canteen's Two-Tier Revenue Report.* By definition, observations in Stratum 1 purportedly have been reviewed and examined by Canteen. In the event that Canteen provides no additional information on their machines that they already analyzed, Plaintiffs' counsel has instructed me to calculate damages and interest based on what appears in Canteen's existing historical records, namely the Two-Tier Revenue Report and Survey Instance Report.

b. *Show that sampled observations are missing and/or incomplete at random.* This approach typically entails conducting statistical comparisons between the sample and parent population. If it can be shown that sampled observations are in fact missing and/or incomplete at random, then the practitioner generally can choose to (i) work with a smaller sample, or (ii) select additional observations at random.

c. *For observations in Stratum 3, assign $0 in damages to the extent that the requested information is missing and/or incomplete.* This approach naturally

[30] Observations in Stratum 1 and Stratum 3 were placed in a random order using the computational program Stata.

yields the most conservative calculation of principal damages and pre-judgment interest.

Each of the above methods ensure that all randomly selected observations are taken into account. This puts the practitioner in a strong position to draw valid statistical inferences about the defined population.

B. Methodology for Calculating Classwide Principal Damages

38. Calculating classwide principal damages entails two processes: (i) collecting, reviewing and analyzing the stratified random sample of data, and (ii) using the results from the stratified random sample to extrapolate classwide principal damages and derive the corresponding confidence intervals. In total, seven steps are involved:

Within the stratified random sample:

- *Step 1*: Examine the sampled observations in the order that they appear in Exhibit 2 herein.
- *Step 2*: Obtain/record additional information about each observation based on photographs of vending machines, namely:[31]
  - Whether the machine is a cashless device
  - Whether the machine has a cash discount sticker
  - Whether the machine has a digital shopping cart
- *Step 3*: Assign $0 in damages to each observation in which (i) the machine is not a cashless device, (ii) the cash discount sticker was already on the machine, and/or (iii) the machine has a digital shopping carts.

[31] My understanding is that Plaintiffs will be serving Canteen with discovery requests to obtain, among other things, (i) images of sampled vending machines, and/or (ii) information in writing about each of the three sub-bullet points in Step 2.

- *Step 4*: For all other observations, use the dollar amounts listed in the Two-Tier Revenue Report to calculate the amount in Upcharges up until the date that the machine was surveyed.[32]

Extrapolating to the defined population:

- *Step 5*: Within each stratum, multiply the average Upcharge in the sample by the number of observations in the defined population. This is the extrapolated amount in Upcharges within each stratum.
- *Step 6*: Add the extrapolated amount of Upcharges in Stratum 1 to the extrapolated amount of Upcharges in Stratum 3.
- *Step 7*: Calculate 90 and 95 percent confidence intervals for the total amount in Upcharges, given the stratified random sampling design and distribution of alleged principal damages among sampled observations.[33]

C. Methodology for Calculating Pre-Judgment Interest

39. Plaintiffs' counsel has advised me that the applicable interest rate varies by state. **Exhibit 3** lists the interest rates for each of the states in which Canteen operates.

40. Extrapolating classwide pre-judgment interest and deriving the corresponding confidence intervals entails seven steps:

Within the stratified random sample:

- *Step 1*: For each sampled machine, identify the state in which the machine is located.

[32] Upcharges in the Two-Tier Revenue Report are listed on a monthly basis. For the month in which the machine is surveyed, Upcharges are pro-rated based on the number of days in the month and up to one day prior to the survey. For example, suppose Upcharges in a given month are $60 and a machine is surveyed on April 6, 2019. There are five days in April prior to this machine being surveyed. Therefore, estimated damages pertaining to this machine during the month of April are (5/30) x $60 = $10.

[33] *See* Appendix Chapters B and C for methodologies for calculating confidence intervals. *See also*, Thompson, pp. 120-121.

- *Step 2*: Using this state's interest rate, calculate pre-judgment interest for each month in which there are principal damages.
- *Step 3*: Repeat Steps 1 and 2 for each sampled observation and each month.
- Step 4: Add pre-judgment interest together across all sampled observations.

By way of example, suppose a randomly sampled machine is from a state in which the applicable interest rate is 7 percent simple per annum. Further suppose that the Upcharges for this sampled machine were $10 in July 2021 and $5 in July 2022. If interest is earned up to August 2023, then pre-judgment interest approximately is equal to the following:

$$7\% \text{ x } (\$10 \text{ x } 2 \text{ years} + \$5 \text{ x } 1 \text{ year}) = \$1.75.$$

Extrapolating to the defined population:

- *Step 5*: Within each stratum, multiply the average pre-judgment interest amount by the number of observations in the defined population. This is the extrapolated amount in pre-judgment interest within each stratum.
- *Step 6*: Add the extrapolated amount of pre-judgment interest in Stratum 1 to the extrapolated amount of Upcharges in Stratum 3.
- *Step 7*: Calculate 90 and 95 percent confidence intervals for the total amount in pre-judgment interest, given the stratified random sampling design and distribution of alleged principal damages among sampled observations.[34]

VII. Potential Damages and Interest Calculations

41. **Exhibit 4** shows Upcharges for each unique combination of cost center and machine number in the stratified random sample.[35] At the outset, the Upcharges in Exhibit 4

[34] *See* Appendix Chapters B and C for methodologies for calculating confidence intervals. *See also*, Thompson, pp. 120-121.

[35] For observations in Stratum 1, alleged invalid Upcharges are calculated through the day prior to the earliest

constitute potential principal damages. Once the sample data are collected, reviewed, and analyzed, I anticipate applying Steps 1 through 4 described in Section VI.B above to calculate principal damages among the sampled observations.

42. **Exhibit 5** shows potential pre-judgment interest for each unique combination of cost center, machine number, and state in the stratified random sample. For a given month with Upcharges, potential pre-judgment interest is calculated starting at the end of that month.[36] Once the sample data are collected, reviewed, and analyzed, I anticipate applying the Steps 1 through 4 described in Section VI.C above to calculate updated pre-judgment interest among the sampled observations.[37]

43. **Table 1** below shows extrapolated potential principal damages and pre-judgment interest, along with corresponding confidence intervals. Extrapolated potential principal damages are calculated using Steps 5 through 7 in Section VI.B above. Likewise, extrapolated potential pre-judgment interest is calculated using Steps 5 through 7 in Section VI.C above. Ultimately, I anticipate providing an updated set of extrapolations analogous to Table 1 once the stratified random sample of observations has been collected, reviewed, and analyzed.

survey date. For observations in Stratum 3, Upcharges are calculated through the end of the Two-Tier Revenue Report.

[36] To the extent that a sampled observation has Upcharges in multiple states prior to the earliest survey date, this sampled observation appears on multiple rows in Exhibit 5.

[37] At the outset, potential pre-judgment interest is calculated through August 7, 2023. Upon request from the Court and/or Plaintiffs' counsel, I can update the date through which pre-judgment interest is earned.

Table 1: Potential Classwide Principal Damages and Pre-Judgment Interest		
Description	**Using CLT-Based Formulas**	**Using Bootstrapping**
Potential Principal Damages		
Extrapolated Total	$14,663,731	$14,661,503
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$12,891,014	$12,974,889
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$12,386,073	$12,564,991
Potential Pre-Judgment Interest		
Extrapolated Total	$5,088,893	$5,089,068
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$4,320,508	$4,354,471
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$4,101,626	$4,165,151
* - Equivalent to the lower bound of a two-sided 90 percent confidence interval		

44. Once the analysis of the sample is complete, I also anticipate determining which confidence interval methodology to use, *i.e.*, CLT or bootstrapping. While it is premature to make a decision in this regard, I can offer the following insights at this time:

- CLT-based confidence intervals generally require a sufficiently large sample size and/or sample data that are not heavily skewed[38]

[38] *See, e.g.*, Appendix A, Figure A.1, Figure A.4, and Table A.2.

- Bootstrapped confidence intervals (referred to as "Percentile Confidence Intervals in Appendix C) only requires a sample of data and knowing the random selection process[39]
- It is equally feasible to calculate both CLT-based and bootstrapped confidence intervals

For all of these reasons, both types of confidence intervals are reported in Table 1 above.

VIII. Concluding Remarks

45. Canteen's historical data are used to define a population of observations. A stratified random sample of observations has been selected. This sample has been presented in a way that allows for straightforward updating once additional information are collected, reviewed, and analyzed. Established statistical methods are used to calculate total potential principal damages and pre-judgment interest. Those same statistical methods will be used to determine total updated potential damages and interest.

46. Should additional, relevant information become available to me in this class action, I am open to incorporating it into my future calculations and opinions.

Brian Kriegler, Ph.D.
August 7, 2023

[39] *See* Appendix C.

APPENDIX CHAPTERS

APPENDIX A: A VALIDATION OF RANDOM SAMPLING AND THE CENTRAL LIMIT THEOREM

I. Introduction

Random sampling is used to reach conclusions about a defined population based on a subset of its observations. It is especially valuable when time and cost constraints only allow for the examination of a small fraction of the defined population. Random samples can be used to estimate population characteristics and the corresponding uncertainty. If the sample is "large enough," then this uncertainty can be determined using a law of statistics known as the Central Limit Theorem ("CLT").

Random sampling has been studied and applied for over a hundred years. Countless textbooks have shown it to be a neutral and unbiased process. It is also a highly efficient process. Nevertheless random sampling is met with some skepticism. How can the practitioner *demonstrate* that random sampling is a neutral and unbiased process? How does the practitioner *know* when a sample is "large enough" to apply the CLT? The answers to these questions lie in four core principles of random sampling:

- Estimates are unbiased no matter what the defined population of data looks like.
- Different populations may require different sample sizes in order to apply the CLT.
- A sample size of a few hundred observations or more almost surely is "large enough" to invoke the CLT.
- Differences between sample means and the population mean decrease as the sample size increases.

This appendix chapter serves two purposes. First, we will prove each of the four core principles listed above. Second, we will offer practical recommendations for justifying statistical inference calculations.

II. Demonstrating Noteworthy Properties of Random Sampling

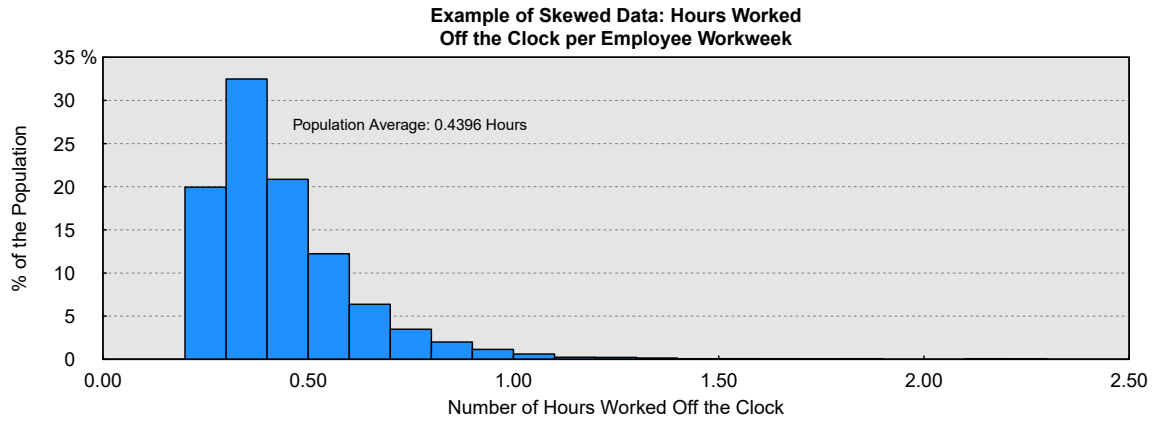
A. Three Populations, Three Targets

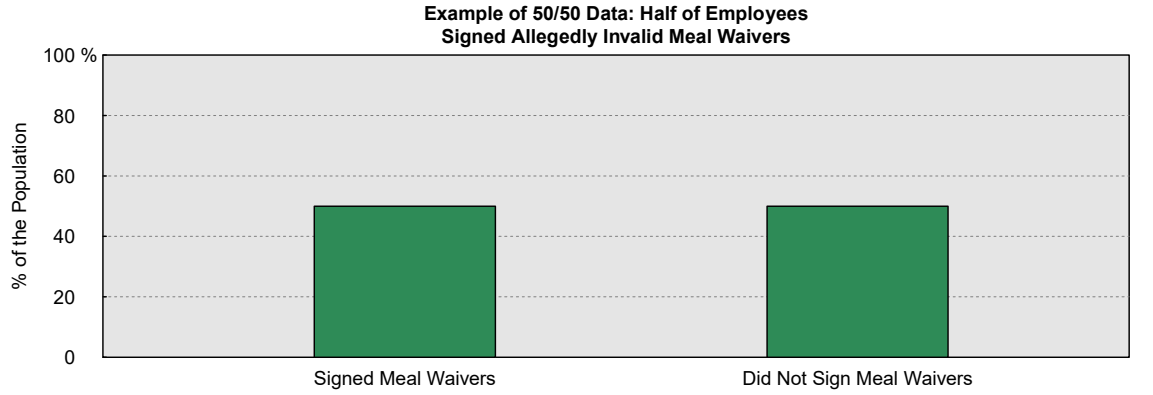
We will work with three populations of data to show how the four core properties of random sampling depend on the nature of the population. These populations exhibit the following fact patterns and data characteristics:

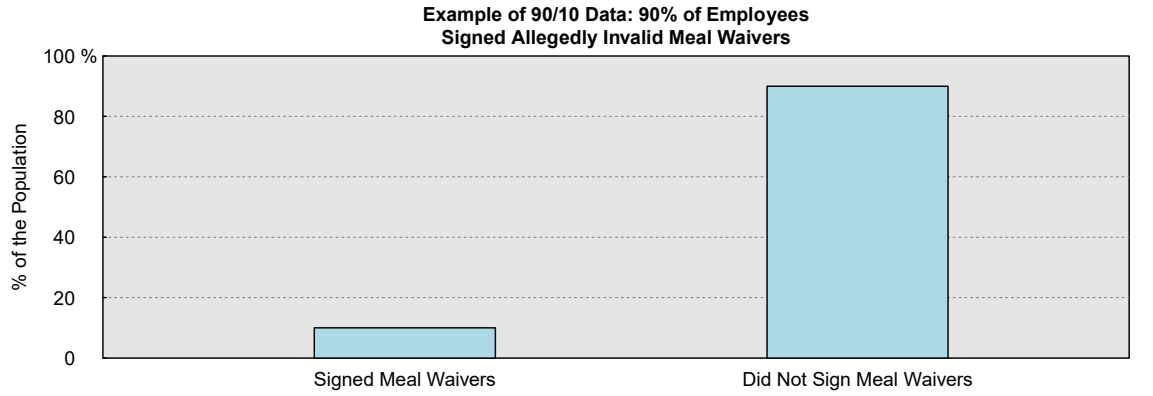
- ("Skewed Data") The first population consists of hours worked off the clock by restaurant employees. These values range from 0.25 hours to 5.0 hours and have an average of 0.440 hours. Approximately 70 percent of values are less than an hour.
- ("50/50 Data") The second population consists of hospital employees. Half of the employees signed allegedly invalid meal break waivers and the remaining employees did not sign meal break waivers.
- ("90/10 Data") The third population also consists of hospital employees. 90 percent of the employees signed allegedly invalid meal break waivers and the remaining employees did not sign meal break waivers.

Figure A.1 below is a graphical representation of these three populations. Skewed Data are shown in medium blue, 50/50 Data are in green, and 90/10 Data are in light blue.

FIGURE A.1
Three Populations of Data







We will apply a sequence of computational steps to each of these three populations. For the time being we will assume that all values in each population are observable and known. This allows us to compare the results from random sampling to the population. We use the following five computational steps to demonstrate that random sampling can be used to draw conclusions about a population:

1. *Identify* a population of data points and calculate the population mean. This is the "target."
2. *Select* a random sample of a desired size and record the sample mean. We will use sample sizes of 20, 50, and 100.
3. *Repeat* step 2 many times. This allows the practitioner to observe virtually all likely sample averages, *a.k.a.* sample means.
4. *Calculate* the average of the sample means and compare it to the "target," *i.e.*, the average of the population from which the sample was randomly selected.
5. *Graph* the sample means in a "histogram"[1] and observe how the sample means are distributed. Statistical practitioners typically refer to the histogram of sample means as a "sampling distribution."

These five steps are used to address two issues. First, we want the average of the sample means to be equal to the "target." Such result proves that random sampling is a neutral and unbiased process. Second, we want to gauge whether the sampling distribution is approximately symmetric and bell-curved. If so, then the sample is "large enough" to rely on the CLT to compute confidence intervals for the population mean. If the histogram is not approximately symmetric and bell-curved, then an alternative method is likely more appropriate for deriving confidence intervals. That topic will be discussed in the next appendix chapter.

Figures A.2, A.3, and A.4 show three sampling distributions. **Figure A.2** is derived from Skewed Data, **Figure A.3** is derived from 50/50 Data, and **Figure A.4** is derived from 90/10 Data.[2] Within each of these figures, the respective histograms are based on a few

[1] A histogram is a graphical display where data are grouped into ranges (*e.g.*, 40 to 49, 50 to 59, etc.) and then plotted as bars. It is similar to a bar graph, except that with a histogram, each bar is for a range of data rather than a specific value.

[2] With the 50/50 and 90/10 Data, a histogram of sample means requires a transformation. Observe that each employee either did or did not sign a meal break waiver. These are not numerical values but rather categorical values. Therefore, the measurement of interest is the *proportion* of employees that signed meal

thousand random samples of 20, 50, and 100 observations. Just as in Figure A.1, results based on Skewed Data are in medium blue, 50/50 Data are in green, and 90/10 data are in light blue. In addition, **Table A.1** and **Table A.2** below show selected results from these graphs.

break waivers. The population mean (proportion) equals the number of employees that signed meal break waivers divided by the number of employees in the population. Likewise, each sample mean is the number of employees that signed meal break waivers divided by the sample size.

FIGURE A.2
Histograms of Sample Means from Skewed Data

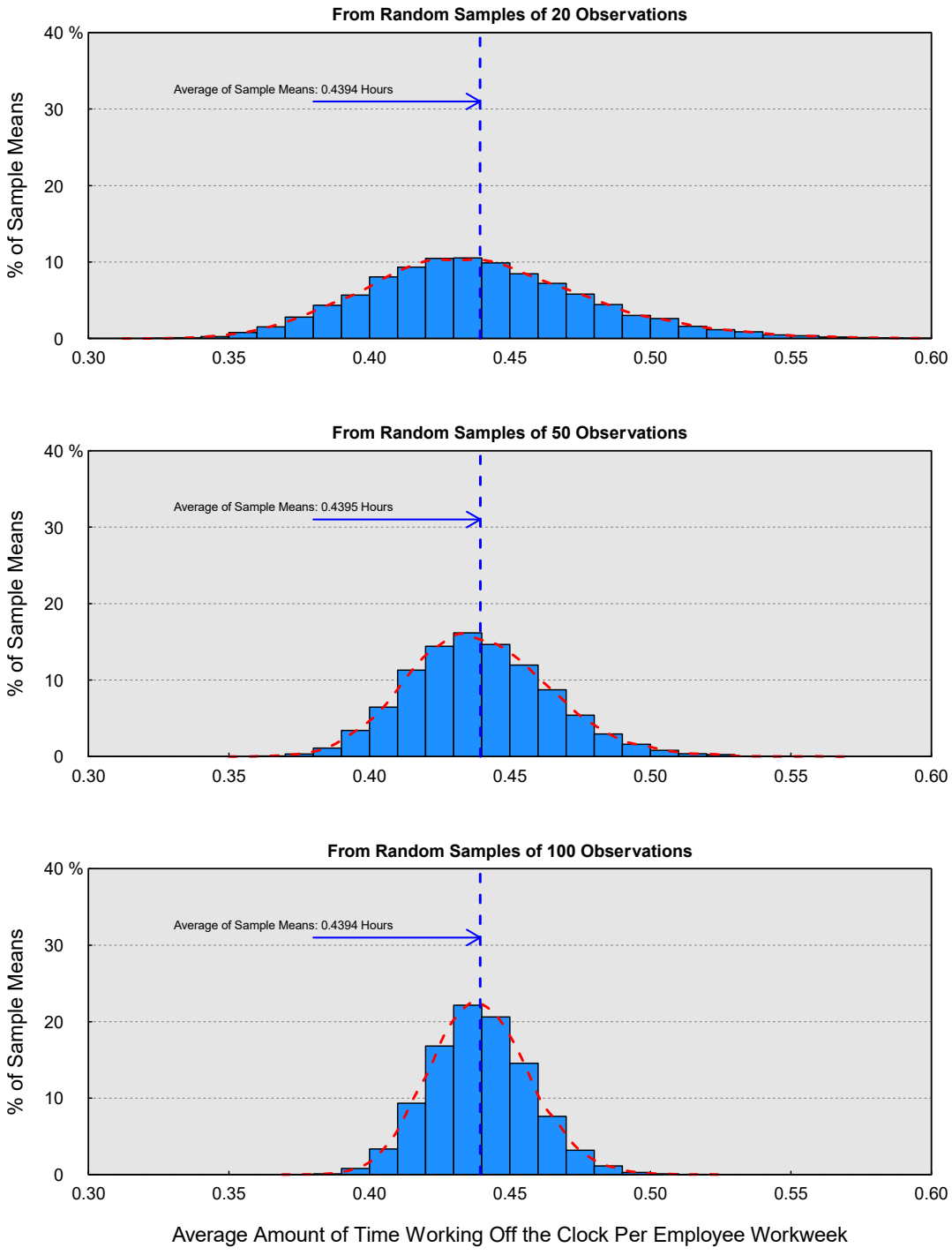


FIGURE A.3
Histograms of Sample Proportions from 50/50 Data

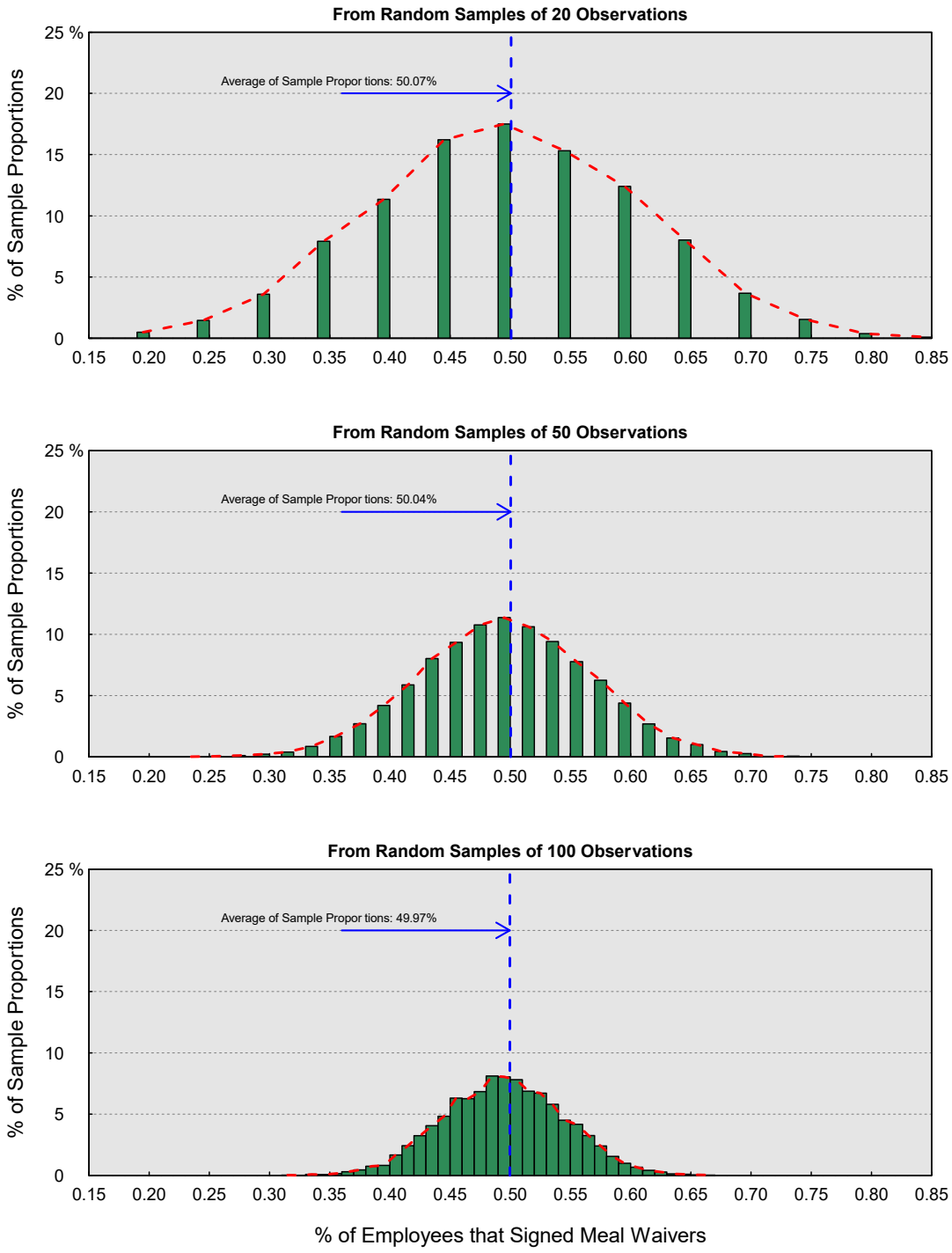


FIGURE A.4
Histograms of Sample Proportions from 90/10 Data

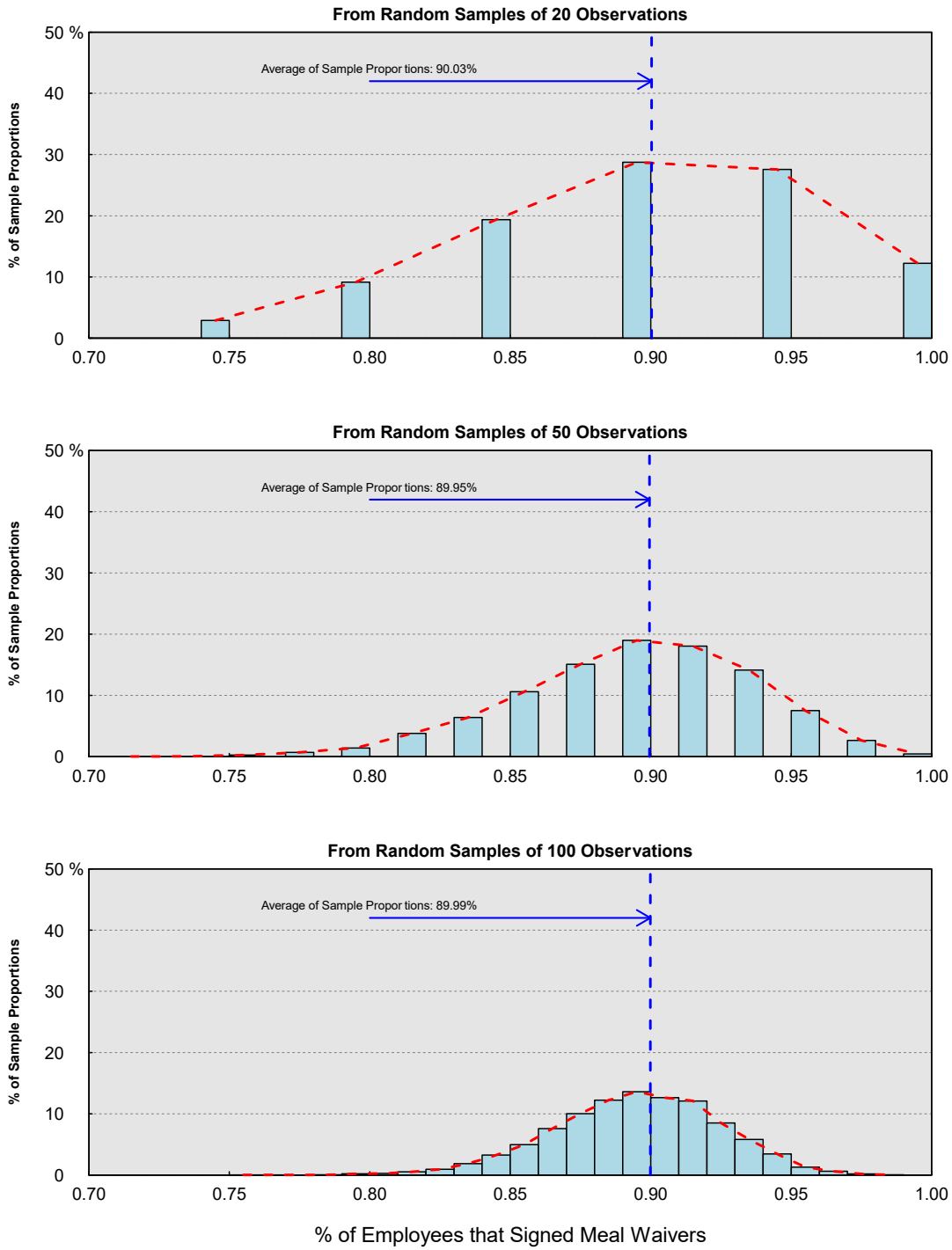


Table A.1: Comparison of Population Means to Averages of Sample Means Shown in Figures A.2, A.3, and A.4			
Population & Mean / Sample Size	Skewed Data (Figure A.2)	50/50 Data (Figure A.3)	90/10 Data (Figure A.4)
	0.440	**0.5000**	**0.9000**
20	0.439	0.5007	0.9003
50	0.440	0.5004	0.8995
100	0.440	0.4997	0.8999

Table A.2: Assessment of Whether the Sampling Distribution is Bell-Curved Shown in Figures A.2, A.3, and A.4			
Population / Sample Size	Skewed Data (Figure A.2)	50/50 Data (Figure A.3)	90/10 Data (Figure A.4)
20	YES	YES	No
50			No
100			Yes

B. Analysis

The figures and tables reveal four fundamental properties about random sampling:

- *First*, for each population and sample size, the average of the sample means is virtually identical to the population mean, hitting the "target." This demonstrates that random sampling is a neutral and unbiased process.

- *Second*, we observe bell-curved histograms using sample sizes of 20 when selected from Skewed Data and 50/50 Data. 90/10 Data require a relatively large sample size in order to achieve a bell-curved histogram. These differences demonstrate that the sample size needed to utilize the CLT depends on the shape of the population of data.

- *Third*, each histogram based on a random sample of 100 observations is symmetric and bell-curved. This result demonstrates that with a "large enough" sample size, the sampling distribution will be bell-curved even if the population is not bell-curved.

- *Fourth*, in each figure, the histograms get taller and narrower as the sample size increases. This shows that sample means are more likely to be closer to the population mean as the sample size increases.

III. Practical Considerations

Thus far we have assumed for demonstrative purposes that we know the values for every observation in the population. This allows us to compare the histogram of sample means to the population mean. However, these circumstances are solely for illustration. Sampling typically is necessitated in practice by the fact that the population of data values *cannot* be viewed in its entirety. Only *one* random sample is selected from a defined population, not thousands. Therefore, we will resolve three pragmatic issues.

A. How Can the Practitioner Make Statements Using a Random Sample When the Population Mean is Unknown?

Referring to Figures A.2 through A.4, each sample mean is essentially a random selection from the sampling distribution. The peak of each histogram is at or close to the population mean. In addition, sample means tend to "bunch up" at or around this value. The sample mean is therefore a neutral and unbiased *estimate* for the population mean.

B. How Can the Practitioner Account for the Fact that Different Samples will Produce Different Population Estimates?

Confidence intervals (discussed in Appendix B through Appendix D) are calculated to address the fact that results vary from one random sample to the next. A confidence interval indicates a range of values that likely contains the population measurement of interest, *e.g.*, the population mean. The CLT provides a series of formulas for computing confidence intervals if the sample is "large enough."

C. How Does the Practitioner Know in Advance What Sample Size will be "Large Enough?"

In this subsection we will describe what statistical practitioners frequently do in order to justify the sample size and method by which they compute confidence intervals.

1. Take a Relatively Large Random Sample

In Table A.2 and in Figures A.2 through A.4 above, we show that a random sample of 100 results in a bell-curved histogram. This is true even when sampling from the 90/10 Data. With rare exceptions--for instance, if 99% of observations have one value and the remaining 1% of observations have another value--a sample of a few hundred or more observations will be more than adequate.

2. Select a Random Sample in Multiple Phases

We have established that the shape of the population impacts what sample size is needed to yield a bell-curved histogram. Because a random sample is a neutral and unbiased representation of the population, its shape will generally resemble that of the population. Typically after examining a few dozen observations, the practitioner can get a sense of what sample size will ultimately be needed. If the data are highly unbalanced, like the 90/10 data, then a relatively large sample will be required. If not, then the required sample size will be more modest.

3. Apply an Alternative Method to the CLT

Suppose that a random sample is not "large enough" to invoke the CLT, *e.g.*, a sample of 20 from a population of 90/10 Data. Confidence intervals can still be determined, just not using the CLT. One approach for doing so builds on "resampling." This approach will be discussed in the Appendix C.

IV. Concluding Remarks about Random Sampling

The advantages of random sampling cannot be understated. It gives the practitioner formal and scientific bases to estimate population characteristics and to compute confidence intervals. It is hard to argue that the computations explained in this appendix chapter are biased and/or not neutral. This puts the practitioner in a strong position to make statements about the defined population.

APPENDIX B: DERIVATION OF CONFIDENCE INTERVAL FORMULAS WHEN APPLYING THE CENTRAL LIMIT THEOREM

Statisticians typically use two types of confidence intervals for the population mean or population proportion: "two-sided" and "one-sided" confidence intervals. A two-sided confidence interval is symmetric around the point estimate (*e.g.*, sample average) of interest; the true value of interest in the population is just as likely to be above as it is below the point estimate. In some cases, the lower bound (or upper bound) on the point estimate may be of particular interest, so the researcher can be confident that the measurement of interest is *above* a certain value (or *below* a certain value). If so, then a one-sided confidence interval may be appropriate. As I demonstrate below, while 95 percent is a commonly used confidence level, other levels can be sufficient in certain circumstances.

Half of the width of a confidence interval--that is, the difference between the population estimate and the lower (or upper) bound--is generally referred to as the "margin of error."[3] Arithmetically, a two-sided confidence interval is generally expressed as:

$$\textit{Sample Average} \pm \textit{Margin of Error}.$$

In addition, a one-sided confidence interval with a lower bound is generally expressed as:

$$\textit{Sample Average} - \textit{Margin of Error}.$$

The margin of error is a byproduct of (i) the sample size, (ii) the variability in the data, and (iii) the desired level of confidence. All things being equal, the confidence interval will be wider if there is a considerable amount of disparity in the data. Conversely, the confidence interval will be tighter as one increases the sample size.

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[3] *See, e.g.*, Moore, D.S., and McCabe, G.P. (1999). *Introduction to the Practice of Statistics.* 3rd Ed. New York: W.H. Freeman. p. 506. (Hereinafter, "Moore and McCabe.") While the term "margin of error" is frequently associated with a 95 percent confidence interval, the fact of the matter is that this term broadly refers to the amount of uncertainty that one can tolerate. *See also*, the definition of "margin of error" on www.stattrek.com. ("The margin of error expresses the maximum expected difference between the true population parameter and a sample estimate of that parameter…For example, a pollster might report that 50% of voters will choose the Democratic candidate. To indicate the quality of the survey result, the pollster might add that the margin of error is ±5%, with a confidence level of 90%.").

From an informational perspective, it is more desirable to have a tighter confidence interval, and along with this, a precise population estimate. At the same time, there are no hard, fast rules in the field of Statistics about what constitutes a "tight enough" confidence interval or "small enough" margin of error. Likewise, there are no hard, fast rules about what *level* of confidence one must use. These depend heavily on the subject matter and the objective(s) of the issue at hand.

As explained in Appendix A, random samples of 20 or more are generally large enough to invoke the Central Limit Theorem. Provided that the sample is "sufficiently large," a two-sided 68 percent confidence interval for the population mean based on a simple random sample is approximately equal to the following:[4]

$$\textit{Sample Average} \pm \textit{Standard Error},$$

where the Standard Error is equal to:

$$\textit{Standard Deviation} \;/\; \sqrt{\textit{Sample Size}}.$$

As the sample size increases, there is less uncertainty about the population more broadly. In addition, with a two-sided 68 percent confidence interval, the margin of error *equals* the standard error.

Similarly, a two-sided 95 percent confidence interval is approximately equal to the following:

$$\textit{Sample Average} \pm 2 \times \textit{Standard Error}.$$

With a two-sided 95 percent confidence interval, observe that the lower bound also corresponds to a one-sided 97.5 percent confidence interval (since 2.5 percent fall below the

---

[4] *See*, *e.g.*, Moore and McCabe (2009):

- p. 72 (showing that 68 percent of the normal distribution is within one standard deviation of the mean, 95 percent of the normal distribution is within two standard deviations of the mean, and 99 percent of the normal distribution is within three standard deviations of the mean).
- p. 402 (explaining that the distribution of the sample mean is nearly normally distributed); and
- pp. 505-506 (defining the standard error as the standard deviation of the sample mean, which is equal to the standard deviation divided by the square root of the sample size).

confidence interval). It follows that, to obtain a *one-sided* 95 percent confidence interval, one must multiply the standard error by a number between 1 and 2, which is a multiplier that varies depending on the sample size. It is well-established that, for sample sizes of at least 30, this number will be between 1.65 and 1.70, depending on the sample size.[5] Thus, in general for a simple random sample, the one-sided 95 percent confidence interval with a lower bound is approximately equal to the following:

Sample Average - 1.7 x *Standard Error*.

[5] *See*, *e.g.*, Moore and McCabe, p. T-11 (showing that the scalar for a 95 percent confidence interval with 30 or more degrees of freedom ranges from 1.65 to 1.70). For these kinds of confidence intervals, degrees of freedom are equal the number of observations minus 1).

APPENDIX C: RESAMPLING AND BOOTSTRAPPING: A ROBUST METHOD FOR DETERMINING CONFIDENCE INTERVALS

I. Introduction

We established in Appendix A that random sampling is a neutral and unbiased process. A random sample's data characteristics will approximate those in the population. If the sample is "large enough," then confidence intervals for the population average can be calculated using well-established formulas based on the Central Limit Theorem ("CLT"). CLT requirements are likely met if the data include at least 30 randomly selected observations.

An alternative method may be desirable if the practitioner cannot confirm that the dataset is "large enough" to apply the CLT. Consider a class action lawsuit in which the Court allows 25 randomly selected class members to testify. Testimony from these people is used to estimate characteristics about the class, *e.g.*, damages per class member, along with the corresponding confidence interval. This sample may not be large enough to invoke the CLT. In this appendix chapter we show one way to derive reliable confidence intervals irrespective of the sample size.

For future reference this CLT-alternative method is called "bootstrapping." It builds on "resampling" the data (also referred to as "sampling with replacement"). We will study three questions in this appendix chapter:

- How are confidence intervals derived using resampling and bootstrapping?
- How do we *know* that these confidence intervals are statistically reliable?
- How do confidence intervals based on resampling compare to those using the CLT?

Observations can be randomly selected multiple times, once, or not at all when sampling with replacement. This is different from the "usual" random sampling *without* replacement in which each observation is selected once or not at all.

Table C.1 lists three pragmatic differences between sampling with and without replacement.

Table C.1: Differences between "Sampling with Replacement" and "Sampling without Replacement"	
Sampling without Replacement	**Sampling with Replacement**
Each observation can only be selected once	There is no restriction on the number of times an observation can be selected
The "observed data" is a randomly selected subset from the defined population	The sample with replacement is selected from--and has the same number of observations as--the observed data
One subset of observations is selected from the defined population	*Many* samples with replacement can be selected from the observed data, *i.e.*, *as if it were the population*

Below is a simple demonstration of sampling with replacement. Consider the commuting time for five randomly selected people. These five people's commute times are 15, 20, 25, 30, and 35 minutes. The average of these times is 25 minutes. Assume that the commute times from the first three samples with replacement are as follows:

- 1st sample with replacement: 15, 15, 20, 35, 35 (average = 24 minutes)
- 2nd sample with replacement: 15, 15, 25, 30, 30 (average = 23 minutes)
- 3rd sample with replacement: 20, 30, 30, 35, 35 (average = 30 minutes)

We will explore how sampling with replacement a large number of times provides valuable results.

II. How is Resampling Used to Derive Confidence Intervals?

Six steps are used to derive confidence intervals from resampled data. Among statistical practitioners, this sequence is commonly referred to as "bootstrapping:"[6]

1. *Determine* which sampling procedure was used to select the observed data, *e.g.*, simple random sampling.

2. *Draw* a random sample with replacement from the observed data using the sampling procedure identified in step 1.

[6] *See*, *e.g.*, Efron, B. and Tibshirani, R.J. (1993). *An Introduction to the Bootstrap*. New York: Chapman & Hall. pp. 168-174. Note that the term "bootstrapping" implies getting into (or out of) a situation using existing resources. In a statistical context, the "existing resources" consist of *one* randomly selected dataset.

3. *Calculate* the "resampled mean."

4. *Repeat* steps 2 and 3 a few thousand times or more. With each repetition, the number of observations should be the same as in the observed data.

5. *Identify* the percentiles of sample means that align with the desired confidence interval.

   Example: Assume that steps 2 and 3 are repeated 10,000 times with the assistance of a computer program. A common goal is to derive "one-sided" and "two-sided" 95 percent confidence intervals. A one-sided 95 percent confidence interval has a single lower bound at the 5th percentile of resampled means. With 10,000 observations, the 5th percentile is the 500th lowest value. A two-sided 95 percent confidence interval ranges from 2.5 percentile to the 97.5 percentile of resampled means. These are at the 250th lowest to the 250th highest value. These are "**Percentile Confidence Intervals.**"[7]

6. *Graph* the histogram of resampled means. This histogram will be symmetric or asymmetric. A symmetric histogram usually indicates that bootstrapping and CLT-based formulas will produce similar confidence intervals. An asymmetric histogram may suggest that bootstrapping produces more reliable confidence intervals.

There are pros and cons to bootstrapping. Bootstrapping only requires two pieces of information: a random sample of data and knowing how these data were selected. There are no requirements about the minimum sample size or population data characteristics. The drawback to bootstrapping is that there is no statistical formula to follow. Percentile Confidence Intervals typically are authenticated based on a review of the computer program that generated the resampled means.

III. Why Does Resampling from the Observed Data Produce Reliable Confidence Intervals?

Bootstrapping yields reliable confidence intervals because of three fundamental characteristics of random samples.

[7] Percentile Confidence Intervals are discussed in Efron and Tibshirani (1993), pp. 168-174. *See also*, *e.g.*, Berk, R.A. (2004) *Regression Analysis: A Constructive Critique*. Thousand Oaks: Sage Publications. pp. 74-76.

- The observed dataset is an unbiased approximation of the population because random sampling is inherently neutral and unbiased
- Multiple random samples drawn from the same population will yield different results
- One observed dataset can be resampled a large number of times to approximate the variation across multiple random samples

IV. Case Study: How Much Time Did Employees Work Off the Clock?

Consider a class action lawsuit consisting of 100,000 employees. The employees allege that they were not paid for all time worked. Alleged work performed "off the clock" must be estimated because the employer does not keep track of this time. It is prohibitively expensive to ask each employee how much work time was not recorded. Instead a random sample of class members is deposed and asked how much time they worked off the clock. These employees' testimony is used to estimate the average--and ultimately total amount--of unrecorded work time across all class members. In addition, there is a need to derive confidence intervals for the population average and total.[8]

Random sampling and bootstrapping are necessitated by the fact that the population average is not known. Setting aside that this fact is unknown to the practitioner, assume that the population consists of 90,000 class members who worked 10 minutes off the clock per workweek. The remaining 10,000 class members worked 60 minutes off the clock per workweek. This works out to an average of 15 minutes per workweek for each class member.

To learn about the population the practitioner selects a random sample of class members who report in deposition their off-the-clock time. This deposition testimony is analyzed after 20, 50, and 100 class members. **Table C.2** shows the results after each stage of sampling.

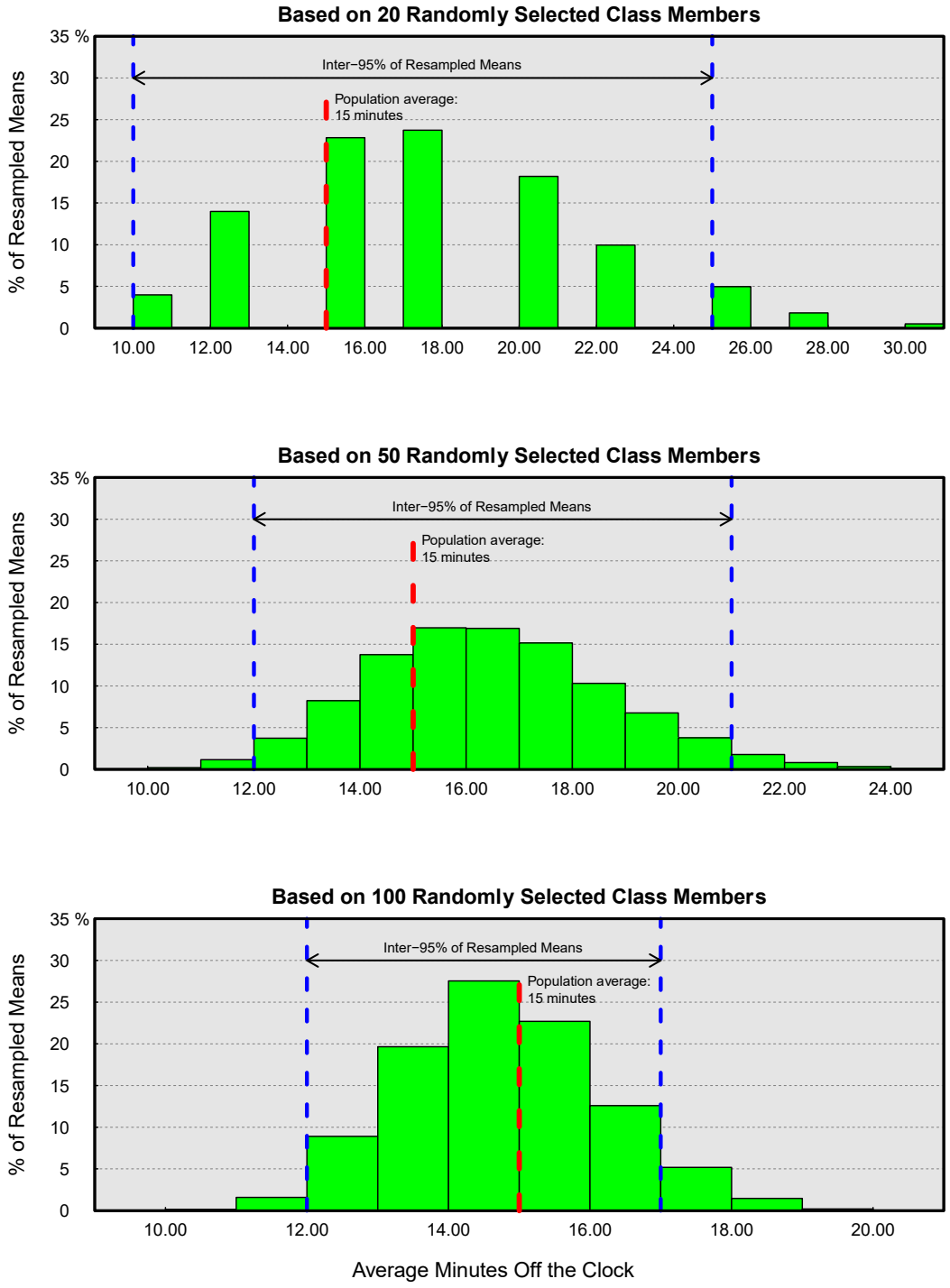
[8] The estimated total amount of time that class members worked off the clock equals the number of class members multiplied by the estimated average.

Table C.2: Illustrative Results Based on a Random Sample of Class Members' Deposition Testimony			
Sample Size	**# People with 10 Minutes Off the Clock**	**# People with 60 Minutes Off the Clock**	**Sample Average**
20	17	3	(17 x 10 + 3 x 60) / 20 = 17.5
50	44	6	(44 x 10 + 6 x 60) / 50 = 16.0
100	91	9	(91 x 10 + 9 x 60) / 100 = 14.5
Population Average (in practice, not observed)	90,000	10,000	(90,000 x 10 + 10,000 x 60) / 100,000 = 15.0

A. Deriving Percentile Confidence Intervals

The practitioner resamples the observed data 10,000 times using the aforementioned bootstrapping steps. 10,000 resampled means are generated in the process. **Figure C.1** below shows three histograms of these resampled means. The three graphs are based on samples of 20, 50, and 100 randomly selected class members. 95 percent of resampled means are between the two blue dotted lines. This also captures the essence of a 95 percent confidence interval. The dotted red line shows the true population average of 15 minutes. The scales on each graph are different because the collection of resampled means gets narrower as the sample size increases.

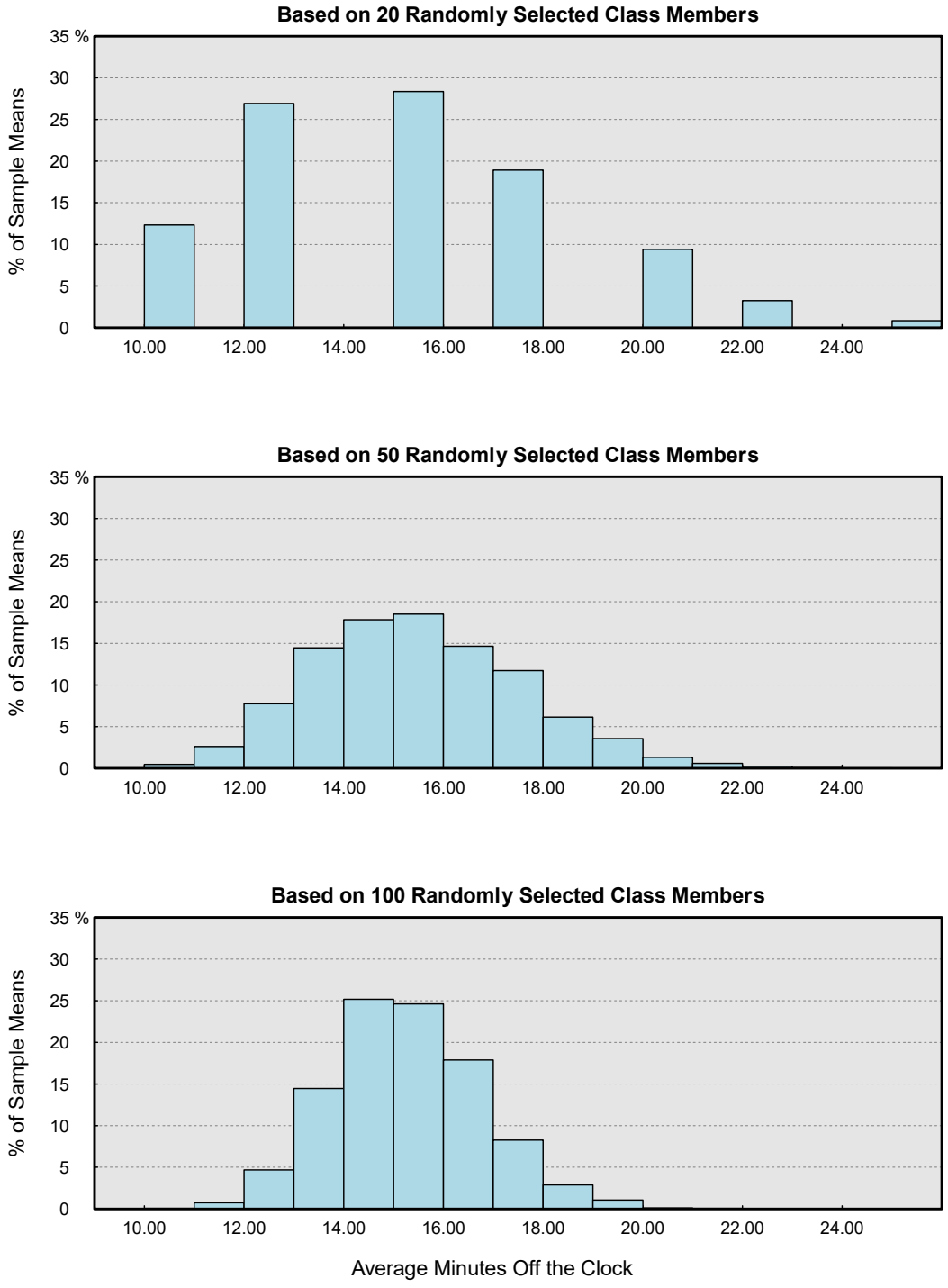
Figure C.1
Histograms of 10,000 Resampled Averages
And Percentile Confidence Intervals for the Classwide Average



B. Verifying that Percentile Confidence Intervals are Statistically Reliable

How do we *know* that the histograms of resampled means selected from the observed data are meaningful? We can find out by comparing Figure C.1 to **Figure C.2** below. Figure C.2 contains histograms of sample means selected from the *population*. Here we are assuming that we know the amount of time that every class member worked off the clock strictly for illustrative and comparative purposes. In reality, random sampling is necessitated by virtue of the fact that this information is unknown.

Figure C.2
Histograms of 10,000 Sample Averages
Assuming that Data Were Available for All Class Members



The histograms in Figure C.1 strongly resemble those in Figure C.2. Both histograms based on 20 observations are asymmetric and disjointed. Both histograms based on 50 observations are slightly asymmetric. Both histograms based on 100 observations are approximately symmetric and bell-curved. The fact that these two figures look so similar confirms that bootstrapping can be used to approximate the true distribution of sample means. It follows that bootstrapping also can be used to derive confidence intervals for the population mean.[9]

C. How Do Percentile Confidence Intervals Compare to CLT-based Confidence Intervals?

Using our practitioner's sample data, **Table C.3** compares Percentile Confidence Intervals with CLT-based confidence intervals[10] for several commonly relied-upon confidence levels: one-sided 95 percent, two-sided 95 percent, and two-sided 99 percent.

[9] Figure C.2 does not include confidence intervals for the population mean. This is intentional. A confidence interval is only needed if the population mean is *unknown*. In this theoretical demonstration, data are available for every person in the population.

[10] The CLT-based formulas for confidence intervals applied in this appendix chapter are approximately the following:

- One-sided 95 percent confidence interval with a lower bound: Sample Mean - 1.7 x Standard Deviation / √Sample Size.
- Two-sided 95 percent confidence interval: Sample Mean ± 2.0 x Sample Standard Deviation / √Sample Size.
- Two-sided 99 percent confidence interval: Sample Mean ± 2.6 x Sample Standard Deviation / √Sample Size.

Table C.3: Comparison of Percentile Confidence Intervals to CLT-based Confidence Intervals Using Case Study Data						
Sample Size & Sample Mean	Confidence Interval Method	One-Sided 95% Interval	Two-Sided 95% Interval		Two-Sided 99% Interval	
		Lower Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
		(Number of minutes working off the clock)				
20 Depositions (Mean = 17.5)	Percentile	10.00	10.00	22.50	10.00	25.00
	CLT	9.05	7.80	22.20	5.16	24.85
	Difference	*0.95*	*2.20*	*0.30*	*4.84*	*0.15*
50 Depositions (Mean = 16.0)	Percentile	12.00	11.00	19.00	10.00	21.00
	CLT	11.41	10.69	19.31	9.26	20.74
	Difference	*0.59*	*0.31*	*0.31*	*0.74*	*0.26*
100 Depositions (Mean = 14.5)	Percentile	12.50	12.50	18.00	11.50	19.00
	CLT	12.50	12.01	17.99	11.04	18.96
	Difference	0.00	0.49	0.01	0.46	0.04
Note: The practitioner does not observe or know that the population mean is 15.00 minutes.						

Differences between Percentile and CLT-based confidence intervals are noticeably large when based on 20 randomly selected class members. The 99 percent confidence interval lower bounds differ by nearly five minutes, and the 95 percent confidence interval lower bounds differ by more than two minutes.[11] These are relatively large differences considering the population average is 15 minutes. Such results suggest that a sample of 20 observations is not enough to apply the CLT. Bootstrapping is especially valuable under these circumstances.

Percentile and CLT-based confidence intervals tend to converge as more depositions are taken and analyzed. Random samples of 100 produce very similar results across confidence interval methodologies. This demonstrates that the practitioner can choose which confidence interval method to apply as the sample size grows. It also supports the notion that the CLT can be used to calculate confidence intervals if the random sample is "sufficiently large."

[11] That is, 10.00 - 5.16 = 4.84 minutes, and 10.00 - 7.80 = 2.20 minutes.

V. Concluding Remarks about Bootstrapped Confidence Intervals

Statistical practitioners have multiple tools for deriving confidence intervals. In Appendix A, we showed that the CLT has sample size requirements for calculating confidence intervals. Bootstrapping is an alternative method that can be applied to any random sample even if the sample size is relatively small.

Resampling and bootstrapping are applicable if the observed data were selected using random sampling. It is tempting to conclude that a small number of observations--such as 20-50 depositions--cannot be used to draw inferences about thousands of people. A small sample may well look different than the defined population. This is why it is so important to calculate, interpret, and rely on confidence intervals when drawing conclusions about the population. Bootstrapping provides an efficient and reliable tool for determining confidence intervals in a broad set of circumstances.

APPENDIX D: AN INTERPRETATION AND VALIDATION OF CONFIDENCE INTERVALS

I. Introduction

In Appendix C, we showed that random samples have numerous advantageous features. Such datasets can be used to reach conclusions about a defined population. The statistical literature has shown random sampling to be a neutral and unbiased process. In Appendix chapters B and C, we discussed formal and scientific methods for deriving confidence intervals ("CIs") for measurements such as the population mean.

By way of example, suppose a random sample of employees are asked how long they are at the workplace before their shift begins. Assume that the 95 percent CI is 20 +/- 7 minutes. The interpretation is that (i) the unbiased estimate for average is 20 minutes, and (ii) we are 95 percent confident that the population average is between 13 and 27 minutes.

Figure D.1 below shows a visual representation of a CI. Each horizontal line shows a CI based on a new random sample. Blue lines straddle the population mean and red lines do not capture the mean. Over a large number (*e.g.*, thousands) of random samples of a specified size, we would expect 95 percent of the horizontal lines to cross the vertical (black) bar signifying the population mean. Equivalently, we can also expect that 5 percent of the horizontal lines will not cross the vertical bar. In this appendix chapter, we will refer to the percentage of intervals that contain the population mean as the "Capture Rate."

FIGURE D.1
Graphical Illustration of 100 Distinct 95 Percent Confidence Intervals

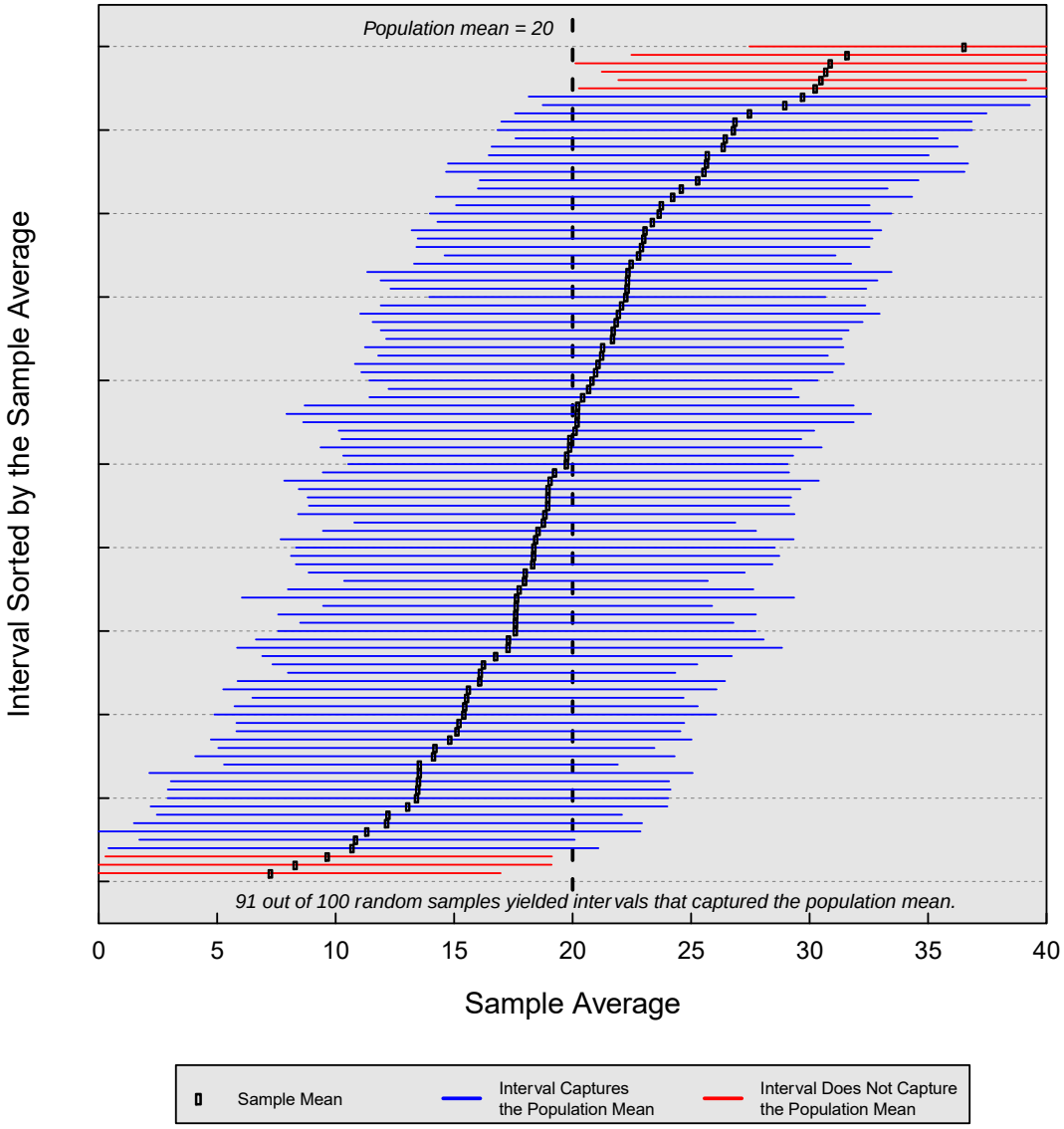


Figure D.1 illustrates three key features of CIs and the Capture Rate. *First*, each random sample produces a different sample average and interval. *Second*, some intervals will not contain the population mean. *Third*, the Capture Rate does not necessarily equal the stated confidence level. In this instance the Capture Rate is 91 percent while the stated confidence level was 95 percent, *i.e.*, a difference of 4 percent.

We will explore the implications of the distance between the Capture Rate and stated confidence level in more detail below. The Capture Rate provides valuable information about a confidence interval. It can be used as a basis for comparison to the desired level of confidence. It also signifies an estimate for the actual level of certainty.

Here are four questions pertaining to the use of CIs and the Capture Rate:

1. How do we design an experiment so that the Capture Rate is compared to the stated confidence level, *e.g.*, 90 or 95 percent?

2. To what extent is the CI reliable if the difference between the Capture Rate and stated confidence level is "relatively large?"

3. How does the Capture Rate compare to the stated confidence level if the underlying data are not symmetric and/or the sample size is small?

4. How do we estimate the Capture Rate based on a random sample of data?

These questions will be addressed using computational simulations. Results will be shown across combinations of (i) four distinct populations, and (ii) four sample sizes, (iii) two methods for calculating CIs, and (iv) two stated confidence levels.[12]

II. The Experiment

Table D.1 below lists nine steps needed to (i) compute the Capture Rate, and (ii) gauge the distance between the Capture Rate and the stated confidence level. The steps shaded in grey apply to both the CLT-based and bootstrapped CIs.

[12] In total there are 64 experiments, *i.e.*, 2 methods x 2 CIs x 4 populations x 4 sample sizes.

Table D.1: Steps Needed to Compare the Capture Rate to the Stated Confidence Level		
Step	**If Using the Central Limit Theorem (CLT)**	**If Using Bootstrapping**
1	*Define* a population and calculate its mean	
2	*State* the desired confidence level(s)	
3	*Select* a random sample of a specified size from the population defined in Step 1	
4	*Compute* the sample mean and sample standard deviation from Step 3	*Generate* thousands of samples with replacement ("resamples") from the random selection in Step 3
5	*Compute* the confidence interval(s) of interest using (i) established confidence interval formulas, and (ii) the sample mean and standard deviation from Step 4	*Identify* the percentiles of resample means that align with the desired confidence level*
6	*Record* whether the confidence interval from Step 5 has captured the population mean computed in Step 1	
7	*Repeat* Steps 3 through 6 thousands of times	
8	*Calculate* the "Capture Rate," *i.e.*, percentage of CIs that include the population mean based on Step 7	
9	*Compare* this percentage to the target confidence level stated in Step 2	
* For instance, if 1,000 resamples were taken, a two-sided 90 percent confidence interval would range from the 50th lowest resample mean to the 50th highest resample mean.		

We will apply the steps listed in Table D.1 using a wide range of statistical circumstances. Specifically, we will:

- *Assume* four hypothetical and distinct populations
- *Select* random samples of 25, 50, 100, and 300 observations
- *Apply* stated confidence levels of 90 and 95 percent
- *Compute* both CLT-based and bootstrapped CIs

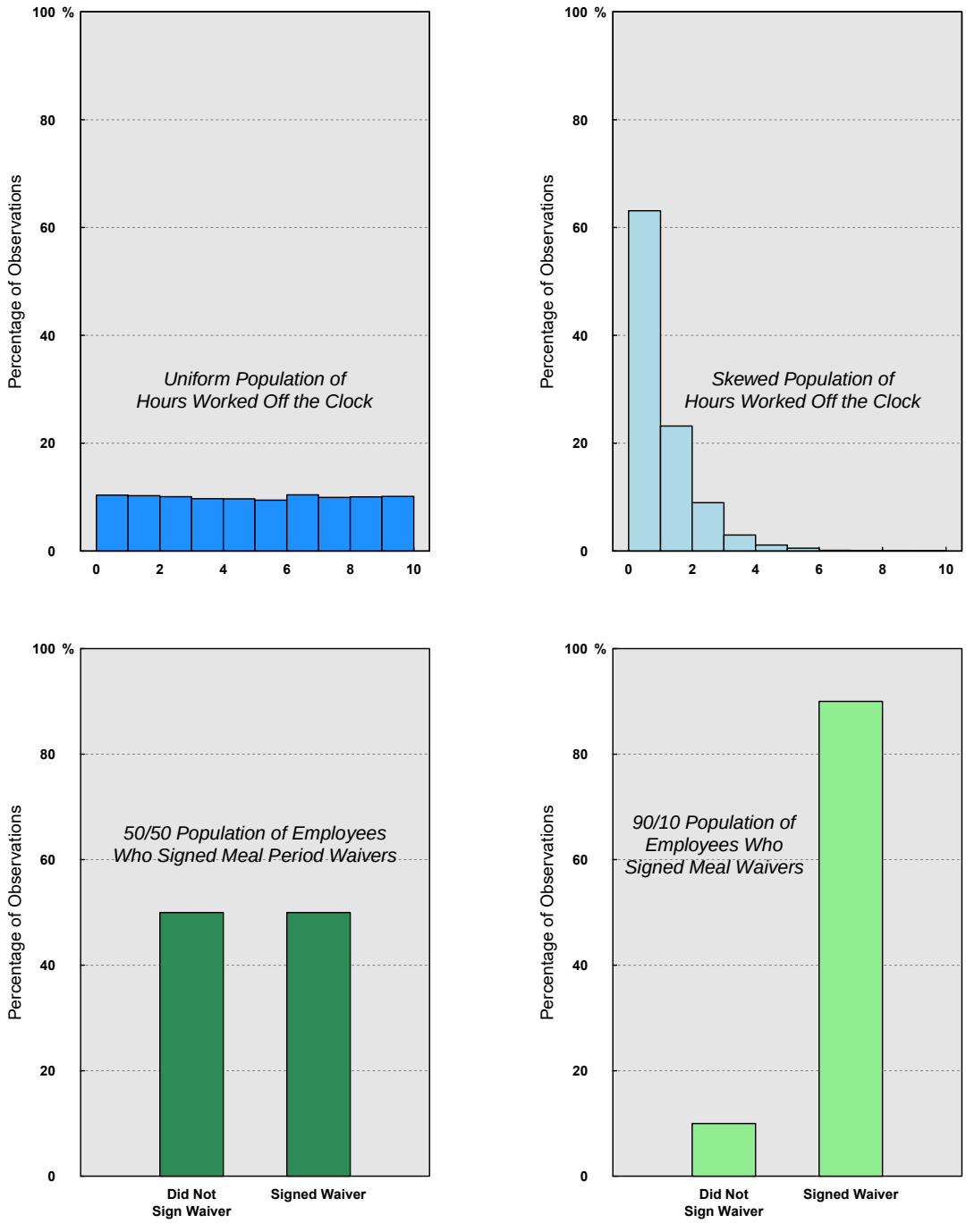
For the time being we will assume that all values in each population are observable and known. The "Practical Considerations" section below includes a discussion about how

the practitioner can apply the aforementioned nine steps using a random sample of data, *i.e.*, when the whole population is not available.

Figure D.2 below shows graphs of each of the four hypothetical and distinct populations. These populations are defined as follows:

- "Uniform Data" - The first population consists of hours worked off the clock by hourly employees. These values range from 0 to 10 with an average of 5 hours. Each data value has roughly the same probability of occurrence.
- "Skewed Data" - The second population consists of hours worked off the clock under a different set of circumstances. These values range from 0 hours to 10 with an average of just 1.0 hour. Approximately 65 percent of values are less than an hour. The remaining 35 percent of values range from 1 to 10 hours.
- "50/50 Data" - The third population consists of nonexempt employees. Half of the employees signed allegedly invalid meal break waivers and the remaining employees did not sign meal break waivers.
- "90/10 Data" - The fourth population also consists of nonexempt employees under a different set of circumstances. 90 percent of the employees signed allegedly invalid meal break waivers and the remaining 10 percent of employees did not sign meal break waivers.

FIGURE D.2
Four Distinct Data Populations:
Uniform, Skewed, 50/50, and 90/10 Data



III. Summary of Results and Graphical Representations

This section includes results pertaining to the distance between the Capture Rate and stated confidence level for each population and sample size. Such comparisons are performed using CLT-based and bootstrapped confidence intervals. In summary:

Results from CLT experiments:

- Capture Rates for 90% CIs range from 87 to 92 percent
- Capture Rates for 95% CIs range from 88 to 96 percent

Results from bootstrapping experiments:

- Capture Rates for 90% CIs range from 86 to 92 percent
- Capture Rates for 95% CIs range from 91 to 96 percent

Results across all experiments:

- Differences between the Capture Rate and stated confidence level tend to decrease as the sample size grows[13]
- The skewed and 90/10 population yield relatively larger differences between the Capture Rate and the stated confidence level[14]
- The uniform distribution yields the smallest differences between the Capture Rate and the stated confidence level[15]
- The largest difference between the Capture Rate is 6.7 percent and the stated confidence level

[13] For the four sample sizes, the median differences between the Capture Rate and stated confidence level are as follows: 25 observations - 1.8 percent, 50 observations - 1.6 percent, 100 observations - 0.8 percent, and 300 observations - 0.7 percent.

[14] When the population is skewed, the median difference between the Capture Rate and stated confidence level is 1.5 percent. When the population is unbalanced, this difference is 1.65 percent.

[15] When the population is uniformly distributed, the median difference between the Capture Rate and stated confidence level is 0.3 percent.

Figure D.3 and **Figure D.4** below show graphical representations of these results. The red dotted line denotes the stated confidence level, *i.e.*, the "target." Figure D.3 includes output using CLT-based formulas for CIs, and Figure D.4 is based on bootstrapped CIs. These graphs use the same color scheme as in Figure D.2 to denote each distinct population.[16] For a given population, sample size, and CI method, the Capture Rates tend to straddle and/or be close to the stated level of confidence.

[16] The uniform population is in blue, the skewed population is in light blue, the 50/50 population is in medium green, and the 90/10 population is in light green.

FIGURE D.3
Capture Rates When Applying the CLT

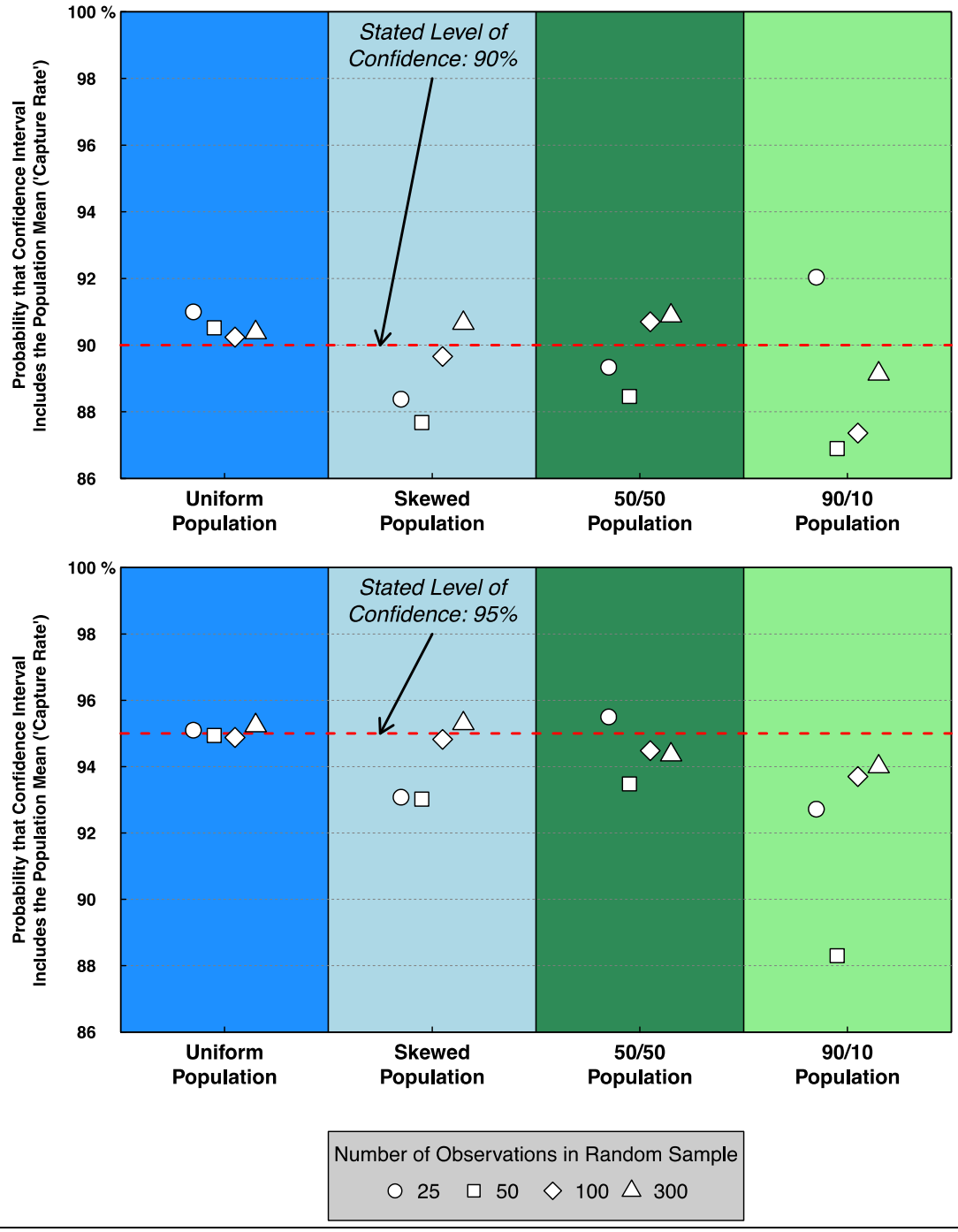
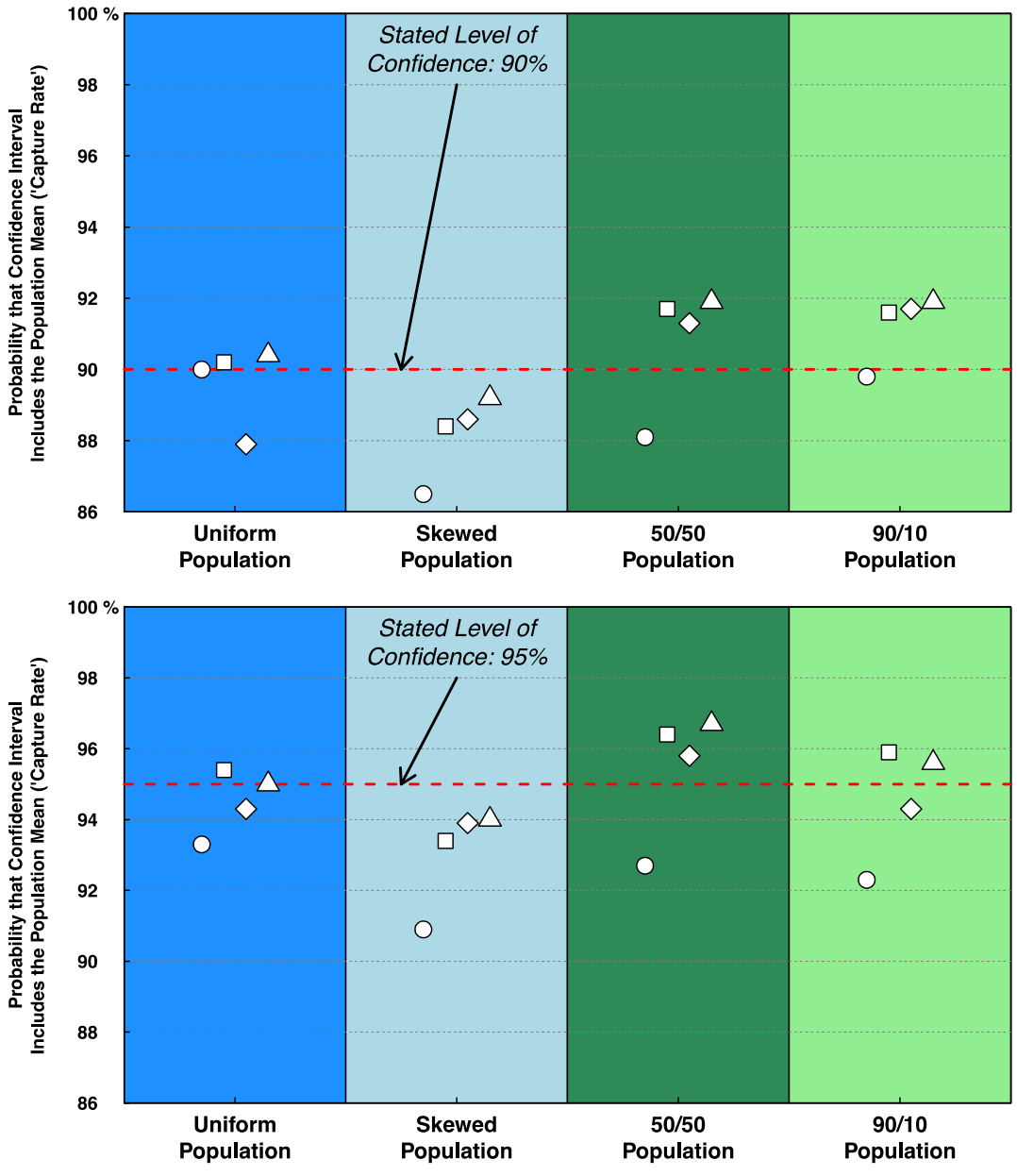


FIGURE D.4

Capture Rates When Applying Bootstrapping



IV. Practical Considerations when Deriving the Capture Rate and Interpreting Confidence Intervals

Thus far we have assumed that we know the values for every observation in the population. However, these circumstances are solely for illustrative purposes. In practice, it can be challenging to derive the Capture Rate because the practitioner only gets to collect/analyze *one* random sample, not hundreds or thousands. How might the experimental process and results described above be used given that only limited data are available? Below are four recommendations that can aid in the sampling process and/or CI interpretation.

A. Estimate the Capture Rate by Creating a Proxy for the Population and Proceeding with the Nine Steps Listed Above

A random sample can generate a "stand-in" for the population. Suppose the defined population includes 10,000 observations and a random sample of 100 observations has been analyzed. That sample can be used to simulate a dataset of 10,000 analyzed observations. Each observation can be selected multiple times, once, or not at all.[17] Subsequently, the practitioner can calculate the Capture Rate and compare it to the stated confidence level.

B. Assess Whether the Likely Value of the Capture Rate is "High Enough"

By way of example, consider a 95 percent CI based on a random sample of 25 observations. The results herein suggest that the actual level of confidence may be closer to 90 percent.[18] Depending on the circumstances and/or industry standards, 90 percent may be considered sufficiently high.[19] If so, then this random sample of 25 observations can be used to make inferences about the population mean and its range of likely values.

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[17] Statisticians frequently refer to this type of selection as "sampling with replacement."

[18] Bootstrapping is likely a more appropriate CI method given a sample size of 25 observations. Applying a stated confidence level of 95 percent, the bootstrapped Capture Rates are as follows: Uniform Data - 93.3%, Skewed Data - 90.9%, 50/50 Data - 92.7%, and 90/10 Data - 92.3%.

[19] *See*, *e.g.*, the CMS Medicare Program Integrity Manual ("[i]n most situations the lower limit of a one-sided 90 percent confidence interval shall be used as the amount of overpayment to be demanded for recovery from the provider or supplier." URL: https://www.cms.gov/Regulations-and-Guidance/Guidance/Manuals/downloads/pim83c08.pdf.

C. Recognize the Shape of Data Distribution in the Sample

If the random sample produces a nearly symmetric distribution of data, this supports the notion that the Capture Rate and the stated confidence level are relatively close to one another. Conversely, an asymmetric data distribution may imply that the actual level of confidence is lower than its target.

D. Increase the Sample Size so that the Capture Rate is More Likely to Approach the Stated Confidence Level.

Ideally, the Capture Rate equals or is very close to the stated confidence level. The results herein suggest that this is likely to be the case when the random sample includes several hundred observations or more.

V. Concluding Remarks about the Interpretation and Validation of Confidence Intervals

This appendix chapter includes a method that enables statistical practitioners to: (i) account for the fact that each random sample yields a unique estimate and margin of error, (ii) estimate the rate at which the CI will capture the population mean, and (iii) compare the Capture Rate to the stated confidence level. Numerous experiments, which run the gamut in terms of population shapes and sample sizes, have been performed. The computational process and results provide powerful information about CIs and their interpretation.

For some practitioners, it may be tempting to dismiss a random sample and corresponding CIs if the data are asymmetric and/or the sample size is small. The results presented above provide compelling evidence that neither of these issues impede the calculation of reliable confidence intervals. Ultimately, it may be informative to derive and report the Capture Rate in order to gauge the actual level of confidence. Doing so places the practitioner on solid ground when making statements about the defined population.

ATTACHMENT 3

IN THE UNITED STATES DISTRICT COURT
FOR THE EASTERN DISTRICT OF MISSOURI
EASTERN DIVISION

GEORGE MOORE, VIRGINIA CARTER, JAMES JILEK, FRANCIS JAYE, and SEAN MADELMAYER, **Plaintiffs,** **v.** **COMPASS GROUP USA, INC., D/B/A CANTEEN,** **Defendant.**	**No. 4:18-CV-01962-SEP**

SUPPLEMENTAL EXPERT REPORT OF BRIAN KRIEGLER, PH.D.

Econ ONE Research, Inc.

August 11, 2023

Suite 800
550 South Hope Street
Los Angeles, California 90071

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LIST OF SUPPLEMENTAL EXHIBITS

I. Introduction

1. I have personal knowledge of the facts set forth in this expert report, except where otherwise specified. If called to testify to these facts as a witness in this action, I would so testify.

2. I have been retained by the Plaintiffs in *George Moore, et al. v. Compass Group USA, d/b/a Canteen*, Case No. 4:18-CV-01962-SEP, in the United States District Court for the Eastern District of Missouri, Eastern Division.

3. Except where specified otherwise, the terminology and methodology utilized in this supplemental expert report are the same as in the Expert Report of Brian Kriegler, Ph.D., dated August 7, 2023 ("Kriegler Report").

4. The purpose of this supplemental expert report is to provide a stratified random sample of machines located in California ("California Stratified Random Sample").

II. Deriving/Defining the California Sampled Population

5. "California Stratum 1" is the sub-population of all machines in Stratum 1 that were in California at or before the earliest survey date. There are 4,555 combinations of cost center and machine numbers that fit this description. Note that total Upcharges in California through the earliest survey date in this stratum are equal to $1,339,716.82.

6. "California Stratum 3" is the sub-population of all machines in Stratum 3 that were or are located in California. There are 306 combinations of cost center and machine numbers that fit this description. Note that total Upcharges in California are equal to $64,033.08.

III. Selecting the California Stratified Random Sample

7. All observations in California Stratum 1 are placed in a random order. Subsequently, the first 65 observations in this random order are selected.

8. Similarly, all observations in California Stratum 3 are placed in a random order. Subsequently, the first 35 observations in this random order are selected.

9. The California-specific stratified sample of 100 observations is shown in **Supplemental Exhibit 1**. This exhibit is analogous to Exhibit 2 in the Kriegler Report. Within each stratum, the sampled observations are to be reviewed/analyzed in the order that they appear in this list.

IV. Potential Damages and Interest Calculations Pertaining to California

10. **Supplemental Exhibit 2** shows Upcharges for each unique combination of cost center and machine in the California stratified random sample. This exhibit is analogous to Exhibit 4 in the Kriegler Report.

11. **Supplemental Exhibit 3** shows potential pre-judgment interest for each unique combination of cost center and machine number in the California stratified random sample. This exhibit is analogous to Exhibit 5 in the Kriegler Report.

12. **Supplemental Table 1** below shows extrapolated potential principal damages and pre-judgment interest pertaining to the California Sampled Population, along with corresponding confidence intervals. This table is analogous to Table 1 in the Kriegler Report.

Supplemental Table 1: Potential Principal Damages and Pre-Judgment Interest Pertaining to Machines that Are or Were in California		
Description	**Using CLT-Based Formulas**	**Using Bootstrapping**
Potential Principal Damages		
Extrapolated Total	$1,542,324	$1,542,852
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$1,088,508	$1,116,427
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$957,404	$1,007,564
Potential Pre-Judgment Interest		
Extrapolated Total	$645,323	$646,032
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$450,875	$463,283
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$394,700	$423,071
* - Equivalent to the lower bound of a two-sided 90 percent confidence interval		

V. Concluding Remarks

13. The same methodologies presented in the Kriegler Report are applied to the subset of machines that are or were in California.

14. Should additional, relevant information become available to me in this class action, I am open to incorporating it into my future calculations and opinions.

Brian Kriegler, Ph.D.
August 11, 2023

ATTACHMENT 4

IN THE UNITED STATES DISTRICT COURT
FOR THE EASTERN DISTRICT OF MISSOURI
EASTERN DIVISION

GEORGE MOORE, VIRGINIA CARTER, JAMES JILEK, FRANCIS JAYE, and SEAN MADELMAYER, **Plaintiffs,** **v.** **COMPASS GROUP USA, INC., D/B/A CANTEEN,** **Defendant.**	**No. 4:18-CV-01962-SEP**

SECOND SUPPLEMENTAL EXPERT REPORT OF BRIAN KRIEGLER, PH.D.

Econ ONE Research, Inc.

October 12, 2023

Suite 800
550 South Hope Street
Los Angeles, California 90071

TABLE OF CONTENTS

LIST OF EXHIBITS

I. Introduction

1. I have personal knowledge of the facts set forth in this expert report, except where otherwise specified. If called to testify to these facts as a witness in this action, I would so testify.

2. I have been retained by the Plaintiffs in *George Moore, et al. v. Compass Group USA, d/b/a Canteen*, Case No. 4:18-CV-01962-SEP, in the United States District Court for the Eastern District of Missouri, Eastern Division.

3. I am the same Brian Kriegler, Ph.D., who previously has provided analyses and opinions in the following settings:

    - Expert Report of Brian Kriegler, Ph.D., dated August 7, 2023 ("Kriegler Report")
    - Supplemental Expert Report of Brian Kriegler, Ph.D., dated August 11, 2023 ("Kriegler Supplemental Report")[1]
    - Deposition of Brian Kriegler, Ph.D., dated August 23, 2023 ("Kriegler Deposition")

    Collectively, the Kriegler Report and Kriegler Supplemental Report are referred to as the "Kriegler Reports."

4. The same terminology and methodology introduced in the Kriegler Report is applied herein, with the following modifications:

    - Stratum 1 is referred to as "Nationwide Stratum 1"
    - Stratum 3 is referred to as "Nationwide Stratum 3"

5. In this class action lawsuit, there have been three key events since the Kriegler Deposition that pertain to my analysis/opinions:

[1] This report was followed up by an errata, dated August 25, 2023.

- *First*, Canteen produced additional data/documents consisting of (i) an updated Survey Instance Report that includes 263,016 rows of data,[2] and (ii) photographs for sampled machines in Nationwide Stratum 1 and/or in California Stratum 1.[3]

- *Second*, Canteen provided "Interrogatory Responses" in which they provided pertinent information about sampled machines in Nationwide Stratum 3 and in California Stratum 3.[4]

- *Third*, Canteen's expert, David Kalat, submitted a report dated September 18, 2023 ("Kalat Report"). Therein, Mr. Kalat provided an analysis of the sampled observations in Nationwide Stratum 1 and in California Stratum 1. *See* Kalat Report, Exhibit 4.

6. The purpose of this report is to provide alleged classwide damages and interest using a combination of (i) the methodologies set forth in the Kriegler Report, (ii) the random sample selections presented in the Kriegler Reports, (iii) Canteen's recent data production and interrogatory responses, and (iv) the analyses and opinions presented in the Kalat Report.

II. Evaluation of the Kalat Report

A. Areas of Agreement and/or that are Not Contested

7. As an initial matter, there is a significant amount of convergence between the Kriegler Reports and the Kalat Report. In particular:

[2] *See* CG-0063607, which was included in CG028. Note that the Survey Instance Report referenced in the Kriegler Report includes 246,943 rows of data. *See* Kriegler Report, ¶ 17.

[3] *See* CG-0063608 through CG-0064129, which were included in CG028. Canteen also produced an Excel spreadsheet that matched each bates-stamped photograph to the file name as it appeared in the updated Survey Instance Report. The name of that Excel spreadsheet, as I received it, was titled "CG028 bates and file names.xlsx."

[4] Compass Group USA, Inc.'s Responses and Objections to Plaintiff's Interrogatories Regarding Vending Machines, dated September 8, 2023, Attachment A, ROG 1 and ROG 2 (hereinafter, "Interrogatory Responses").

- The Kalat Report does not dispute that random sampling provides a neutral and unbiased selection process.
- The Kalat Report does not appear to include any impactful critiques of the sampling designs set forth in the Kriegler Reports.
- Mr. Kalat reviewed/analyzed photos of sampled machines, a process that was recommended in the Kriegler Report.[5]
- The Kalat Report utilizes each of the two statistical approaches for calculating principal damages that are set forth in the Kriegler Reports.[6]

B. The Kalat Report's Analysis of Nationwide Stratum 1 and of California Stratum 1

8. Among other things, Exhibit 4 to the Kalat Report includes an analysis of the sampled observations in Nationwide Stratum 1 and in California Stratum 1. These results indicate whether there was a cash discount sticker at the time that the machine was surveyed. To summarize, the Kalat Report concluded the following:

In Nationwide Stratum 1:

- The Kalat Report includes an analysis of 207 out of 250 sampled machines.[7]
- 181 out of 207 sampled machines in Nationwide Stratum 1 did not have a cash discount sticker prior to being surveyed.[8]

[5] Kriegler Report, § VI.B.

[6] *See*, *e.g.*, Kalat Report, ¶ 81.

[7] *See*, *e.g.*, Kalat Report, ¶ 62 ("…[T]here are 207 unique Stratum [1] machines for which an image designated as "BEFORE" was provided….").

[8] Kalat Report, ¶ 67 ("The two-tier revenue collected by the sample population of **207 Stratum [1]** machines nationwide totals $46,910.83. After removing the revenue contributed by the **26 machines** for which the photographic review confirmed had displayed a Cash Discount Sticker, the updated total revenue for the sample population is $40,391.75.") (bolded emphasis added). 207 - 26 = 181.

- The Kalat Report extrapolates damages using the results from the 207 sampled machines and extrapolating to the Nationwide Stratum 1 population. That extrapolated damages amount is $9,813,673.[9]

- Thus, the Kalat Report effectively treats 43 out of 250 sampled machines in Nationwide Stratum 1 as missing at random.[10]

- There are an additional 1,044 machines that have a total of $183,520 in Upcharges. The Kalat Report adds these this dollar amount to arrive at an estimated total of $9,997,193 in alleged principal damages owed to the proposed Nationwide class. [11]

In California Stratum 1:

- The Kalat Report includes an analysis of 53 out of 65 sampled machines.[12]

- 30 out of 53 sampled machines in California Stratum 1 did not have a cash discount sticker prior to being surveyed.[13]

- The Kalat Report extrapolates damages using the results from the 53 sampled machines and extrapolating to the California Stratum 1 population. That extrapolated damages amount is $751,045.[14]

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[9] *See*, *e.g.*, Kalat Report, ¶ 79.

[10] *See* Kalat Report, ¶¶ 67-68. The average Upcharge across 207 sampled machines is multiplied by the number of machines in Nationwide Stratum 1 to arrive at the extrapolated total of $9,813,673.

[11] Kalat Report, ¶ 70 ("…I add the newly identified two-tier revenue of $183,520 from the additional 1,044 machines in Stratum [1] to the figure calculated above ($195.13*50293). **Together these come to collective extrapolated damages for the full Stratum [1] population of $9,997,193.**"). *See also*, Kalat Report, ¶ 81 (showing nationwide calculations that include $183,520).

[12] *See*, *e.g.*, Kalat Report, ¶ 62 ("I also observed the availability of "BEFORE" photographs for 53 of the 65 machines identified in [Dr. Kriegler's] sample for California-based Stratum [1] machines….").

[13] Kalat Report, ¶ 71 ("The two-tier revenue collected by the sample population of 53 Stratum I machines in California totals $16,153. In my examination of the photographs, I identified that **23 of these 53 machines** showed Cash Discount Stickers in the 'BEFORE' images.") (bolded emphasis added). 53 - 23 = 30.

[14] Kalat Report, ¶ 72.

- Thus, the Kalat Report effectively treats 12 out of 65 sampled machines in California Stratum 1 as missing at random.[15]

- There are an additional 114 machines that have a total of $16,398 in Upcharges. The Kalat Report adds these this dollar amount to arrive at an estimated total of $767,443 in alleged principal damages owed to the proposed California class.[16]

9. Looking ahead to Section V, my classwide damages and interest calculations are derived using the results from the Kalat Report and my analysis of Nationwide/California Stratum 3.

C. The Kalat Report Does Not Include a Quantitative Analysis of Nationwide Stratum 3 or of California Stratum 3

10. Canteen produced information about machines in the Nationwide and/or California Stratum 3 in their interrogatory responses. Section III below discusses these interrogatory responses. Section V below incorporates these interrogatory responses into my classwide damages and interest calculations. Nevertheless, the Kalat Report does not provide any quantitative opinions pertaining to the machines that are in Nationwide Stratum 3 and/or California Stratum 3.

D. Evaluation of the Kalat Report's Classwide Damages Calculations

11. The Kalat Report provides classwide principal damages for Nationwide Stratum 1 and for California Stratum 1. In contrast, Section V below includes principal damages based on both Strata 1 and 3, both for the proposed Nationwide class and the proposed California class.

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[15] *See* Kalat Report, ¶¶ 71-72. The average Upcharge across 53 sampled machines is multiplied by the number of machines in California Stratum 1 to arrive at the extrapolated total of $751,045.

[16] Kalat Report, ¶ 73 ("To arrive at a total figure of collective extrapolated damages for the California Stratum [1] machines, I add the newly identified two-tier revenue of $16,398 from the additional 114 machines in California to the figure calculated above ($164.88*4555). **Together these come to collective extrapolated damages for the full Stratum [1] population of $767,443.**"). *See also*, Kalat Report, ¶ 81 (showing California calculations that include $16,398).

E. Pre-Judgment Interest Calculations are Missing from the Kalat Report

12. The Kalat Report does not provide classwide pre-judgment interest calculations. In contrast, Section V below includes pre-judgment interest for both the proposed Nationwide class and the proposed California class.

III. Evaluation of Canteen's Interrogatory Responses

13. Canteen's "Interrogatory Responses" (defined in paragraph 5 above) includes two spreadsheets. "Attachment A, ROG 1" pertains to the random sample of 150 machines in Nationwide Stratum 3. "Attachment A, ROG 2" pertains to the random sample of 35 machines in California Stratum 3. Each spreadsheet indicates whether sampled machines (i) did/did not have a cash discount sticker, (ii) were/were not cash-only devices, and (iii) did/did not include a digital shopping cart.

14. My review of Canteen's Interrogatory Responses reveals the following results:

In Nationwide Stratum 3 (150 sampled machines):

- 85 out of 150 sampled machines purportedly were analyzed by Canteen.
- 11 out of these 85 sampled machines (i) do not have a cash discount sticker, (ii) are not cash-only devices, and (iii) do not include a digital shopping cart.
- For the remaining 65 sampled machines (*i.e.*, 150 sampled machines minus 85 analyzed machines), Canteen's Interrogatory Responses list "NA" with respect to (i), (ii), and (iii) directly above.

In California Stratum 3 (35 sampled machines):

- 23 out of 35 sampled machines purportedly were analyzed by Canteen.
- 10 out of these 23 sampled machines (i) do not have a cash discount sticker, (ii) are not cash-only devices, and (iii) do not include a digital shopping cart.

- For the remaining 12 sampled machines (*i.e.*, 35 sampled machines minus 23 analyzed machines), Canteen's Interrogatory Responses list "NA" with respect to (i), (ii), and (iii) directly above.

The next section discusses how these results are combined with the sample selection from Nationwide Stratum 3 and from California Stratum 3.

IV. Combining the Exhibits from the Kriegler Reports with the Results from Canteen's Interrogatory Responses and the Kalat Report

15. **Table A** below lists the datasets that are analyzed in order to apply the methodologies set forth in Sections VI.B and VI.C in the Kriegler Report.

Table A: Datasets Used to Calculate Alleged Damages and Pre-Judgment Interest		
Stratum	**From the Kriegler Reports**	**From Canteen**
Proposed Nationwide Class		
Stratum 1	Kriegler Report, Ex. 4 and 5	Kalat Report, Ex. 4 Kalat Report, ¶ 81[1] CG-63607 (updated Survey Instance Report)[2]
Stratum 3	Kriegler Report, Ex. 4 and 5	Interrogatory Responses, Attachment A, ROG 1
Proposed California Class		
Stratum 1	Kriegler Supplemental Report, Ex. 2 and 3	Kalat Report, Ex. 4 Kalat Report, ¶ 81[3] CG-63607 (updated Survey Instance Report)[4]
Stratum 3	Kriegler Supplemental Report, Ex. 2 and 3[5]	Interrogatory Responses, Attachment A, ROG 2

Notes:
[1] - Specifically, $183,520 in alleged principal damages pertaining to the 1,044 additional machines that meet the criteria for Nationwide Stratum 1.
[2] - Specifically, $23,976 in pre-judgment interest pertaining to the 1,044 additional machines that meet the criteria for Nationwide Stratum 1.
[3] - Specifically, $16,398 in alleged principal damages pertaining to the 114 additional machines that meet the criteria for California Stratum 1.
[4] - Specifically, $4,287 in pre-judgment interest pertaining to the 114 additional machines that meet the criteria for California Stratum 1.
[5] - Corrected Upcharges are listed in the errata to the Kriegler Supplemental Report.

16. For each stratum listed in Table A above, datasets are cross-referenced by cost-center and machine number. For example, in Exhibit 4 to the Kriegler Report, the 64th sample selection in Nationwide Stratum 1 is machine number 17634 from cost center 5553. This machine had Upcharges of $26.40 leading up to the earliest survey date. Additionally, Exhibit 5 to the Kriegler Report indicates $6.17 in alleged pre-judgment interest through August 7, 2023. Exhibit 4 to the Kalat Report indicates that this

machine did not have a sticker prior to being surveyed.[17] Therefore, this sampled observation is assigned $26.40 in alleged principal damages and $6.17 in alleged pre-judgment interest.

17. For each of the sampled observations in Nationwide and/or California Stratum 1, principal damages and interest are $0 if the Kalat Report indicates that the machine already had a cash discount sticker at the time that it was surveyed.

18. For each of the sampled observations in Nationwide and/or California Stratum 3, principal damages and interest are $0 if Canteen's Interrogatory Responses indicate that (i) the machine had a cash discount sticker, (ii) the machine was not cashless, and/or (iii) the machine had a digital shopping cart.

19. A randomly sampled machine is treated as missing at random under each of the following circumstances:

- For machines in Nationwide and/or California Stratum 1, the "Notes" column in Exhibit 4 to the Kalat Report says "Indeterminate" or "Can't see reader."
- For machines in Nationwide and/or California Stratum 3, Canteen's Interrogatory Response is listed as "NA."
- For machines in either stratum in the Nationwide and/or California sample, no photograph was produced.

This approach is consistent with the Kalat Report that is summarized in Section II.B above.

20. **Second Supplemental Exhibit 1** lists alleged monetary principal damages and pre-judgment interest for each sampled observation that (i) was in the Nationwide stratified random sample, and (ii) was reviewed by Mr Kalat. Similarly, **Second Supplemental Exhibit 2** lists alleged monetary principal damages and pre-judgment interest for each sampled observation that (i) was in the California stratified random sample, and (ii) was listed in Canteen's Interrogatory Responses.

[17] The corresponding photo for this particular sampled machine is CG-0063881.

V. Alleged Classwide Damages and Pre-Judgment Interest

21. Tables B through E below show alleged classwide principal damages and pre-judgment interest.[18] In each table:

a. The numbers are calculated using (i) the methodologies set forth in Section VI.B and VI.C to the Kriegler Report, (ii) the cross-referencing methodology described in Section IV above and the data sources referenced therein.

b. The extrapolated total signifies an unbiased statistical estimate of alleged classwide damages/interest.

c. Each confidence interval calculation signifies an "at least" amount of alleged classwide dollars owed, with a specified degree of certainty.

A. The Proposed Nationwide Class

22. **Table B** below shows alleged principal damages and pre-judgment interest for the proposed Nationwide class. Each of the numbers in Table B cover the combination of Nationwide Stratum 1 and Nationwide Stratum 3. This table reveals the following results, among other things:

- Using bootstrapping, the unbiased statistical estimate of alleged classwide principal damages is $9,890,345.
- Using bootstrapping, alleged classwide principal damages is at least $8,313,708 with 90 percent certainty and is at least $7,928,961.
- Using bootstrapping, the unbiased statistical estimate of alleged classwide principal damages plus pre-judgment interest is $13,565,547.
- Using bootstrapping, alleged classwide principal damages plus pre-judgment interest is at least $11,337,290 with 90 percent certainty and at least $10,776,856 with 95 percent certainty.

[18] Just as in the Kriegler Report, pre-judgment interest is calculated through August 7, 2023.

Table B: Alleged Nationwide Principal Damages and Pre-Judgment Interest Not Including 1,044 Additional Machines in Nationwide Stratum 1		
Description	**Using CLT-Based Formulas**	**Using Bootstrapping**
Alleged Principal Damages		
Extrapolated Total	$9,887,282	$9,890,345
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$8,270,889	$8,313,708
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$7,809,977	$7,928,961
Alleged Principal Damages Plus Pre-Judgment Interest		
Extrapolated Total	$13,561,475	$13,565,547
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$11,273,029	$11,337,290
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$10,620,481	$10,776,856
* - Equivalent to the lower bound of a two-sided 90 percent confidence interval.		

23. **Table C** is analogous to Table B. The distinction is that Table C accounts for 1,044 additional machines in Nationwide Stratum 1. These additional machines result in $183,520 in additional alleged principal damages and $23,976 in additional pre-judgment interest.

Table C: Alleged Nationwide Principal Damages and Pre-Judgment Interest Including 1,044 Additional Machines in Nationwide Stratum 1		
Description	**Using CLT-Based Formulas**	**Using Bootstrapping**
Alleged Principal Damages		
Extrapolated Total	$10,070,802	$10,073,865
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$8,454,409	$8,497,228
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$7,993,497	$8,112,481
Alleged Principal Damages Plus Pre-Judgment Interest		
Extrapolated Total	$13,768,971	$13,773,043
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$11,480,525	$11,544,786
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$10,827,977	$10,984,352
* - Equivalent to the lower bound of a two-sided 90 percent confidence interval.		

1. Comparison of Results Using CLT-based Formulas Versus Bootstrapping

24. Alleged monetary awards for the proposed Nationwide class are not sensitive to the statistical method that is used. For example, in terms of classwide principal damages, the difference between CLT-based and bootstrapped lower bounds of a 1-sided 90

percent confidence interval is $3,063. This difference constitutes less than 0.05 percent percent of the classwide total.[19]

B. The Proposed California Class

25. **Table D** is analogous to Table B. The distinction is that Table D pertains to the proposed California class.

Table D: Alleged California Principal Damages and Pre-Judgment Interest Not Including 114 Additional Machines in California Stratum 1		
Description	**Using CLT-Based Formulas**	**Using Bootstrapping**
Alleged Principal Damages		
Extrapolated Total	$786,242	$784,890
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$382,077	$418,639
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$264,803	$371,281
Alleged Principal Damages Plus Pre-Judgment Interest		
Extrapolated Total	$1,067,584	$1,065,126
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$571,728	$609,181
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$427,849	$534,375
* - Equivalent to the lower bound of a two-sided 90 percent confidence interval.		

[19] Both $3,063 / $9,887,282 and $3,063 / $9,890,345 are equal to approximately 0.03 percent.

26. **Table E** is analogous to Table D. The distinction is that Table E accounts for 114 additional machines in California Stratum 1. These additional machines result in $16,398 in additional alleged principal damages and $4,287 in additional pre-judgment interest.

Table E: Alleged Principal Damages and Pre-Judgment Interest in California Including 114 Additional Machines in California Stratum 1		
Description	**Using CLT-Based Formulas**	**Using Bootstrapping**
Alleged Principal Damages, Including Additional Machines Identified in the Kalat Report		
Extrapolated Total	$802,640	$801,288
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$398,475	$435,037
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$281,201	$387,679
Alleged Principal Damages Plus Pre-Judgment Interest		
Extrapolated Total	$1,088,269	$1,085,811
Lower Bound of a 1-Sided 90 Percent Confidence Interval	$592,413	$629,866
Lower Bound of a 1-Sided 95 Percent Confidence Interval*	$448,534	$555,060
* - Equivalent to the lower bound of a two-sided 90 percent confidence interval.		

1. *Comparison of Results Using CLT-based Formulas Versus Bootstrapping*

27. For each measurement (principal damages and pre-judgment interest) and for each confidence interval, CLT-based formulas and bootstrapping produce different results. For example, Table E reports that the one-sided 90 percent confidence interval in damages plus interest is $592,413 using CLT-based formulas and $629,866 using

bootstrapping. This signifies a difference of $37,453 and approximately 6 percent of each confidence interval calculation.[20]

28. From a statistical perspective, my recommendation is to focus on the bootstrapped calculations. I have reached this position based on the following statistical considerations:

- The distribution of each dollar amount is highly unbalanced. Across California Strata 1 and 3, there are 76 sampled machines for which Canteen provided additional information.[21] Of these, 40 sampled machines yield $0 in damages, 15 sampled machines yield less than $100 in damages, 24 sampled machines yield between $100 and $1,000 in damages, and 1 sampled machine yields over $3,500 in damages.[22]

- Appendix A to the Kriegler Report demonstrates that in order to invoke the CLT, a relatively larger sample size is needed when the data are highly skewed.[23]

- There are 53 sampled/analyzed machines in California Stratum 1 and 23 sampled/analyzed machines in California Stratum 3. The statistical literature dictates that a stratified random sample of this size is equivalent to a simple random sample of approximately 50-55 observations.[24]

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[20] That is, $37,453 / $588,126 = 6.4 percent, and $37,453 / $622,579 = 6.0 percent.

[21] 53 of these sampled machines are from California Stratum 1, and 23 of these sampled machines are from California Stratium 3.

[22] The distribution of pre-judgment interest follows a similar pattern. 40 sampled machines yield $0 in interest, 26 sampled machines yield less than $100 in interest, 12 sampled machines yield between $100 and $300 in interest, and 2 sampled machine yields over $500 in interest.

[23] *See* Kriegler Report, Figure A.4 and Table A.1.

[24] *See*, *e.g.*, Thompson, Steven K. (2002). *Sampling.* 2nd Ed. New York: Wiley, p. 121. Therein, the formula for the number of degrees of freedom for a stratified random sample is shown. Using this formula, the California stratified sample has 52 degrees of freedom. In terms of sample size, the interpretation is that the California stratified random sample is equivalent to a simple random sample of 53 observations (*i.e.*, 52+1).

Note that the Nationwide stratified sample has 206 degrees of freedom, which is equivalent to a simple random sample of 207 observations. Under these circumstances, both CLT-based formulas and

- Appendix D to the Kriegler Report suggests that bootstrapped confidence intervals tend to be more accurate when (i) the sample of data are highly skewed, and (ii) the sample includes approximately 50 observations.[25]

- Appendix Chapters C and D to the Kriegler Report demonstrate that bootstrapping provides a statistically reliable method for deriving confidence intervals even when the sample size is relatively small.[26]

VI. Concluding Remarks

29. The methodologies set forth in the Kriegler Report have been applied as intended. Alleged principal damages and pre-judgment interest are calculated both for each proposed class. There is a significant amount of convergence between the parties in terms of (i) the results among the sampled observations, and (ii) the statistical methodologies used to calculate monetary awards and corresponding confidence intervals.

30. Using bootstrapping, the unbiased statistical estimate of alleged principal damages plus pre-judgment interest for the proposed Nationwide class is $13,773,043. Damages plus interest are at least $11,544,786 with 90 percent confidence and at least $10,984,352 with 95 percent confidence. For the proposed California class, the unbiased statistical estimate of alleged principal damages plus pre-judgment interest is $1,085,811. Damages plus interest are at least $629,866 with 90 percent confidence and at least $555,060 with 95 percent confidence.

31. From a statistical perspective, bootstrapping and the CLT yield substantively similar results for the proposed Nationwide class. My recommendation is to focus on bootstrapped confidence intervals for the prosposed California class given the highly skewed data distribution and its relatively small sample size.

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boostrapping are viable options for calculating confidence intervals.

[25] *See* Kriegler Report, Figures D.3 and D.4. The "square" points signify random samples of 50 observations. For random samples of this size bootstrapped confidence intervals tend to be closer to the target red dotted line. This is especially true when the data are "skewed" or from a "90/10" population.

[26] *See, e.g.*, Kriegler Report, Table C.3 and Figure D.4.

32. Should additional, relevant information become available to me in this class action, I am open to incorporating it into my future calculations and opinions.

Brian Kriegler, Ph.D.
October 12, 2023

ATTACHMENT 5A

Stratified Random Sample of Combinations of Cost Center and Machine Number in Florida

Random Order Within Stratum	Cost Center	Machine Number	Earliest Survey Date (Stratum 1 Only)
Within Florida Stratum 1			
Florida Stratum 1 - 1	5080	66801	08/20/2019
Florida Stratum 1 - 2	5080	66461	04/25/2019
Florida Stratum 1 - 3	5047	66019	04/11/2019
Florida Stratum 1 - 4	5073	66149	06/08/2019
Florida Stratum 1 - 5	5073	97343	08/27/2019
Florida Stratum 1 - 6	5073	97392	04/26/2019
Florida Stratum 1 - 7	5064	96366	07/09/2019
Florida Stratum 1 - 8	5564	94030	06/27/2019
Florida Stratum 1 - 9	5064	65184	06/13/2019
Florida Stratum 1 - 10	5564	94362	06/18/2019
Florida Stratum 1 - 11	5047	66807	06/11/2019
Florida Stratum 1 - 12	5073	68976	05/16/2019
Florida Stratum 1 - 13	5073	98055	05/18/2019
Florida Stratum 1 - 14	5064	63824	05/03/2019
Florida Stratum 1 - 15	5073	97130	05/24/2019
Florida Stratum 1 - 16	5064	61425	04/04/2019
Florida Stratum 1 - 17	5047	94251	06/19/2019
Florida Stratum 1 - 18	5544	93029	05/24/2019
Florida Stratum 1 - 19	5080	66580	04/02/2019
Florida Stratum 1 - 20	5545	90829	05/14/2019
Florida Stratum 1 - 21	5073	90339	06/03/2019
Florida Stratum 1 - 22	5047	94186	05/01/2019
Florida Stratum 1 - 23	5545	72274	08/19/2019
Florida Stratum 1 - 24	5064	97430	05/07/2019
Florida Stratum 1 - 25	5080	93604	08/16/2019
Florida Stratum 1 - 26	5085	60475	05/03/2019
Florida Stratum 1 - 27	5073	67654	06/08/2019
Florida Stratum 1 - 28	5085	61224	04/26/2019
Florida Stratum 1 - 29	5047	94941	07/12/2019
Florida Stratum 1 - 30	5545	95564	06/12/2019
Florida Stratum 1 - 31	5564	94181	03/29/2019
Florida Stratum 1 - 32	5564	94485	06/27/2019
Florida Stratum 1 - 33	5064	60537	05/28/2019
Florida Stratum 1 - 34	5564	66225	03/29/2019
Florida Stratum 1 - 35	5085	97014	07/03/2019

Stratified Random Sample of Combinations of Cost Center and Machine Number in Florida

Random Order Within Stratum	Cost Center	Machine Number	Earliest Survey Date (Stratum 1 Only)
Florida Stratum 1 - 36	5545	98038	05/28/2019
Florida Stratum 1 - 37	5047	66301	03/27/2019
Florida Stratum 1 - 38	5073	96540	05/28/2019
Florida Stratum 1 - 39	5064	97877	05/02/2019
Florida Stratum 1 - 40	5064	63139	05/03/2019
Florida Stratum 1 - 41	5073	67424	06/04/2019
Florida Stratum 1 - 42	5085	97040	04/10/2019
Florida Stratum 1 - 43	5080	61081	04/25/2019
Florida Stratum 1 - 44	5064	63603	06/07/2019
Florida Stratum 1 - 45	5073	91401	05/16/2019
Florida Stratum 1 - 46	5073	97869	06/11/2019
Florida Stratum 1 - 47	5047	66124	03/27/2019
Florida Stratum 1 - 48	5544	60064	08/22/2019
Florida Stratum 1 - 49	5545	97931	04/08/2019
Florida Stratum 1 - 50	5545	97578	05/21/2019
Florida Stratum 1 - 51	5080	94984	01/04/2022
Florida Stratum 1 - 52	5064	90508	04/10/2019
Florida Stratum 1 - 53	5064	65217	08/21/2019
Florida Stratum 1 - 54	5064	92852	04/19/2019
Florida Stratum 1 - 55	5064	90213	05/20/2019
Florida Stratum 1 - 56	5545	64277	04/29/2019
Florida Stratum 1 - 57	5545	97618	06/11/2019
Florida Stratum 1 - 58	5085	60123	04/10/2019
Florida Stratum 1 - 59	5047	66207	05/08/2019
Florida Stratum 1 - 60	5085	61216	04/15/2019
Florida Stratum 1 - 61	5064	69075	04/09/2019
Florida Stratum 1 - 62	5064	94502	04/10/2019
Florida Stratum 1 - 63	5064	63311	05/22/2019
Florida Stratum 1 - 64	5544	90395	05/17/2019
Florida Stratum 1 - 65	5073	96725	05/14/2019
Within Florida Stratum 3			
Florida Stratum 3 - 1	5073	60364	-
Florida Stratum 3 - 2	5545	66777	-
Florida Stratum 3 - 3	5047	95110	-
Florida Stratum 3 - 4	5073	98381	-

Stratified Random Sample of Combinations of Cost Center and Machine Number in Florida

Random Order Within Stratum	Cost Center	Machine Number	Earliest Survey Date (Stratum 1 Only)
Florida Stratum 3 - 5	5073	60585	-
Florida Stratum 3 - 6	5064	98957	-
Florida Stratum 3 - 7	5073	60488	-
Florida Stratum 3 - 8	5073	60282	-
Florida Stratum 3 - 9	5080	94931	-
Florida Stratum 3 - 10	5073	60662	-
Florida Stratum 3 - 11	5564	66496	-
Florida Stratum 3 - 12	5073	60460	-
Florida Stratum 3 - 13	5545	60655	-
Florida Stratum 3 - 14	5545	61479	-
Florida Stratum 3 - 15	5085	26039	-
Florida Stratum 3 - 16	5073	98706	-
Florida Stratum 3 - 17	5064	98739	-
Florida Stratum 3 - 18	5085	99402	-
Florida Stratum 3 - 19	5564	66504	-
Florida Stratum 3 - 20	5545	90060	-
Florida Stratum 3 - 21	5073	97634	-
Florida Stratum 3 - 22	5064	65770	-
Florida Stratum 3 - 23	5073	69349	-
Florida Stratum 3 - 24	5073	98336	-
Florida Stratum 3 - 25	5047	67662	-
Florida Stratum 3 - 26	5073	60421	-
Florida Stratum 3 - 27	5064	99260	-
Florida Stratum 3 - 28	5073	98364	-
Florida Stratum 3 - 29	5073	98809	-
Florida Stratum 3 - 30	5064	98265	-
Florida Stratum 3 - 31	5064	98906	-
Florida Stratum 3 - 32	5073	98611	-
Florida Stratum 3 - 33	5073	60700	-
Florida Stratum 3 - 34	5073	98474	-
Florida Stratum 3 - 35	5073	98492	-

ATTACHMENT 5B

Stratified Random Sample of Combinations of Cost Center and Machine Number in South Carolina

Random Order Within Stratum	Cost Center	Machine Number	Earliest Survey Date (Stratum 1 Only)
Within South Carolina Stratum 1			
South Carolina Stratum 1 - 1	5902	66693	05/16/2019
South Carolina Stratum 1 - 2	5273	65198	05/10/2019
South Carolina Stratum 1 - 3	5539	94758	05/06/2019
South Carolina Stratum 1 - 4	5273	65399	05/22/2019
South Carolina Stratum 1 - 5	5539	67161	06/25/2019
South Carolina Stratum 1 - 6	5902	97374	05/15/2019
South Carolina Stratum 1 - 7	5273	66962	06/10/2019
South Carolina Stratum 1 - 8	5539	93072	12/21/2019
South Carolina Stratum 1 - 9	5539	94634	02/14/2023
South Carolina Stratum 1 - 10	5273	93591	08/28/2019
South Carolina Stratum 1 - 11	5273	65104	05/08/2019
South Carolina Stratum 1 - 12	5902	66200	04/01/2019
South Carolina Stratum 1 - 13	5273	67003	08/21/2019
South Carolina Stratum 1 - 14	5539	67368	05/03/2019
South Carolina Stratum 1 - 15	5902	66855	06/10/2019
South Carolina Stratum 1 - 16	5539	92159	06/06/2019
South Carolina Stratum 1 - 17	5273	68197	02/14/2020
South Carolina Stratum 1 - 18	5539	67331	05/03/2019
South Carolina Stratum 1 - 19	5539	94641	02/22/2021
South Carolina Stratum 1 - 20	5902	98234	05/30/2019
South Carolina Stratum 1 - 21	5539	94024	06/19/2019
South Carolina Stratum 1 - 22	5902	92264	06/10/2019
South Carolina Stratum 1 - 23	5273	96675	04/29/2019
South Carolina Stratum 1 - 24	5539	67226	04/26/2019
South Carolina Stratum 1 - 25	5539	92144	01/29/2021
South Carolina Stratum 1 - 26	5539	94520	06/06/2019
South Carolina Stratum 1 - 27	5273	96346	04/12/2019
South Carolina Stratum 1 - 28	5539	67719	01/09/2020
South Carolina Stratum 1 - 29	5273	96408	08/28/2019
South Carolina Stratum 1 - 30	5902	97131	06/25/2019
South Carolina Stratum 1 - 31	5273	66325	06/14/2019
South Carolina Stratum 1 - 32	5273	96389	04/12/2019
South Carolina Stratum 1 - 33	5539	94308	06/06/2019
South Carolina Stratum 1 - 34	5273	66396	08/28/2019
South Carolina Stratum 1 - 35	5273	95535	05/25/2019
South Carolina Stratum 1 - 36	5539	67355	06/06/2019

Stratified Random Sample of Combinations of Cost Center and Machine Number in South Carolina

Random Order Within Stratum	Cost Center	Machine Number	Earliest Survey Date (Stratum 1 Only)
South Carolina Stratum 1 - 37	5273	66921	08/21/2019
South Carolina Stratum 1 - 38	5273	95727	05/07/2019
South Carolina Stratum 1 - 39	5902	95211	04/30/2019
South Carolina Stratum 1 - 40	5902	69122	05/17/2019
South Carolina Stratum 1 - 41	5902	97713	05/29/2019
South Carolina Stratum 1 - 42	5902	98093	06/21/2019
South Carolina Stratum 1 - 43	5902	90138	06/01/2019
South Carolina Stratum 1 - 44	5902	66610	08/06/2021
South Carolina Stratum 1 - 45	5273	68305	05/03/2019
South Carolina Stratum 1 - 46	5902	98173	04/22/2019
South Carolina Stratum 1 - 47	5273	94471	06/18/2019
South Carolina Stratum 1 - 48	5902	97354	06/24/2019
South Carolina Stratum 1 - 49	5539	92871	01/26/2021
South Carolina Stratum 1 - 50	5902	72507	06/04/2019
South Carolina Stratum 1 - 51	5539	67558	05/13/2019
South Carolina Stratum 1 - 52	5539	67393	01/29/2021
South Carolina Stratum 1 - 53	5539	67723	01/25/2021
South Carolina Stratum 1 - 54	5539	67447	05/20/2019
South Carolina Stratum 1 - 55	5273	66797	05/29/2019
South Carolina Stratum 1 - 56	5273	65339	05/24/2019
South Carolina Stratum 1 - 57	5902	98203	05/21/2019
South Carolina Stratum 1 - 58	5902	97510	05/17/2019
South Carolina Stratum 1 - 59	5902	92374	05/30/2019
South Carolina Stratum 1 - 60	5539	92555	04/24/2019
South Carolina Stratum 1 - 61	5902	97706	06/10/2019
South Carolina Stratum 1 - 62	5539	67749	10/26/2021
South Carolina Stratum 1 - 63	5902	69338	05/21/2019
South Carolina Stratum 1 - 64	5539	67237	04/26/2019
South Carolina Stratum 1 - 65	5273	65219	05/23/2019
Within South Carolina Stratum 3			
South Carolina Stratum 3 - 1	5273	68585	-
South Carolina Stratum 3 - 2	5273	68052	-
South Carolina Stratum 3 - 3	5273	72537	-
South Carolina Stratum 3 - 4	5273	96261	-
South Carolina Stratum 3 - 5	5273	21733	-
South Carolina Stratum 3 - 6	5273	96969	-

Stratified Random Sample of Combinations of Cost Center and Machine Number in South Carolina

Random Order Within Stratum	Cost Center	Machine Number	Earliest Survey Date (Stratum 1 Only)
South Carolina Stratum 3 - 7	5273	96943	-
South Carolina Stratum 3 - 8	5273	95340	-
South Carolina Stratum 3 - 9	5141	99863	-
South Carolina Stratum 3 - 10	5273	96945	-
South Carolina Stratum 3 - 11	5273	68625	-
South Carolina Stratum 3 - 12	5273	97011	-
South Carolina Stratum 3 - 13	5273	68583	-
South Carolina Stratum 3 - 14	5273	66920	-
South Carolina Stratum 3 - 15	5141	64745	-
South Carolina Stratum 3 - 16	5141	97732	-
South Carolina Stratum 3 - 17	5273	66316	-
South Carolina Stratum 3 - 18	5273	66787	-
South Carolina Stratum 3 - 19	5273	68070	-
South Carolina Stratum 3 - 20	5273	96985	-
South Carolina Stratum 3 - 21	5273	66487	-
South Carolina Stratum 3 - 22	5273	96908	-
South Carolina Stratum 3 - 23	5273	96993	-
South Carolina Stratum 3 - 24	5141	98890	-
South Carolina Stratum 3 - 25	5273	68603	-
South Carolina Stratum 3 - 26	5273	65261	-
South Carolina Stratum 3 - 27	5273	66725	-
South Carolina Stratum 3 - 28	5273	65063	-
South Carolina Stratum 3 - 29	5273	68630	-
South Carolina Stratum 3 - 30	5539	92659	-
South Carolina Stratum 3 - 31	5273	96988	-
South Carolina Stratum 3 - 32	5539	94680	-
South Carolina Stratum 3 - 33	5273	65666	-
South Carolina Stratum 3 - 34	5273	96974	-
South Carolina Stratum 3 - 35	5273	68627	-

ATTACHMENT 6A

Upcharges Among Randomly Selected Combinations of Cost Center and Machine Number in Florida

Random Order Within Stratum	Cost Center	Machine Number	Upcharges
Within Florida Stratum 1 - Upcharges in Florida are calculated through the day prior to the earliest survey date			
Florida Stratum 1 - 1	5080	66801	$ 2.82
Florida Stratum 1 - 2	5080	66461	40.58
Florida Stratum 1 - 3	5047	66019	1,014.93
Florida Stratum 1 - 4	5073	66149	124.22
Florida Stratum 1 - 5	5073	97343	28.50
Florida Stratum 1 - 6	5073	97392	11.23
Florida Stratum 1 - 7	5064	96366	278.92
Florida Stratum 1 - 8	5564	94030	4.17
Florida Stratum 1 - 9	5064	65184	323.80
Florida Stratum 1 - 10	5564	94362	21.93
Florida Stratum 1 - 11	5047	66807	964.57
Florida Stratum 1 - 12	5073	68976	332.79
Florida Stratum 1 - 13	5073	98055	30.49
Florida Stratum 1 - 14	5064	63824	1,835.55
Florida Stratum 1 - 15	5073	97130	153.20
Florida Stratum 1 - 16	5064	61425	158.10
Florida Stratum 1 - 17	5047	94251	16.14
Florida Stratum 1 - 18	5544	93029	172.60
Florida Stratum 1 - 19	5080	66580	2,740.30
Florida Stratum 1 - 20	5545	90829	25.55
Florida Stratum 1 - 21	5073	90339	229.41
Florida Stratum 1 - 22	5047	94186	831.00
Florida Stratum 1 - 23	5545	72274	105.00
Florida Stratum 1 - 24	5064	97430	84.50
Florida Stratum 1 - 25	5080	93604	160.48
Florida Stratum 1 - 26	5085	60475	532.28
Florida Stratum 1 - 27	5073	67654	177.58
Florida Stratum 1 - 28	5085	61224	127.02
Florida Stratum 1 - 29	5047	94941	110.12
Florida Stratum 1 - 30	5545	95564	204.66
Florida Stratum 1 - 31	5564	94181	9.08
Florida Stratum 1 - 32	5564	94485	109.87
Florida Stratum 1 - 33	5064	60537	531.64
Florida Stratum 1 - 34	5564	66225	5.90
Florida Stratum 1 - 35	5085	97014	205.20
Florida Stratum 1 - 36	5545	98038	920.10
Florida Stratum 1 - 37	5047	66301	115.55
Florida Stratum 1 - 38	5073	96540	22.54
Florida Stratum 1 - 39	5064	97877	42.73

Upcharges Among Randomly Selected Combinations of Cost Center and Machine Number in Florida

Random Order Within Stratum	Cost Center	Machine Number	Upcharges
Florida Stratum 1 - 40	5064	63139	3,442.15
Florida Stratum 1 - 41	5073	67424	512.19
Florida Stratum 1 - 42	5085	97040	163.87
Florida Stratum 1 - 43	5080	61081	258.86
Florida Stratum 1 - 44	5064	63603	379.50
Florida Stratum 1 - 45	5073	91401	1,673.40
Florida Stratum 1 - 46	5073	97869	125.00
Florida Stratum 1 - 47	5047	66124	301.89
Florida Stratum 1 - 48	5544	60064	22.00
Florida Stratum 1 - 49	5545	97931	118.50
Florida Stratum 1 - 50	5545	97578	236.99
Florida Stratum 1 - 51	5080	94984	6.33
Florida Stratum 1 - 52	5064	90508	1,740.50
Florida Stratum 1 - 53	5064	65217	454.90
Florida Stratum 1 - 54	5064	92852	289.80
Florida Stratum 1 - 55	5064	90213	68.75
Florida Stratum 1 - 56	5545	64277	377.22
Florida Stratum 1 - 57	5545	97618	730.40
Florida Stratum 1 - 58	5085	60123	482.92
Florida Stratum 1 - 59	5047	66207	450.68
Florida Stratum 1 - 60	5085	61216	186.05
Florida Stratum 1 - 61	5064	69075	16.70
Florida Stratum 1 - 62	5064	94502	280.63
Florida Stratum 1 - 63	5064	63311	378.15
Florida Stratum 1 - 64	5544	90395	538.73
Florida Stratum 1 - 65	5073	96725	79.87
Within Florida Stratum 3 - Upcharges in Florida are calculated through the end of the Two-Tier Revenue Report			
Florida Stratum 3 - 1	5073	60364	$ 1,098.00
Florida Stratum 3 - 2	5545	66777	194.50
Florida Stratum 3 - 3	5047	95110	154.80
Florida Stratum 3 - 4	5073	98381	364.84
Florida Stratum 3 - 5	5073	60585	272.40
Florida Stratum 3 - 6	5064	98957	48.90
Florida Stratum 3 - 7	5073	60488	37.70
Florida Stratum 3 - 8	5073	60282	667.90
Florida Stratum 3 - 9	5080	94931	134.40
Florida Stratum 3 - 10	5073	60662	696.60
Florida Stratum 3 - 11	5564	66496	473.40
Florida Stratum 3 - 12	5073	60460	103.00

Upcharges Among Randomly Selected Combinations of Cost Center and Machine Number in Florida

Random Order Within Stratum	Cost Center	Machine Number	Upcharges
Florida Stratum 3 - 13	5545	60655	271.80
Florida Stratum 3 - 14	5545	61479	205.80
Florida Stratum 3 - 15	5085	26039	1.10
Florida Stratum 3 - 16	5073	98706	134.30
Florida Stratum 3 - 17	5064	98739	258.50
Florida Stratum 3 - 18	5085	99402	1,568.80
Florida Stratum 3 - 19	5564	66504	951.50
Florida Stratum 3 - 20	5545	90060	23.80
Florida Stratum 3 - 21	5073	97634	979.60
Florida Stratum 3 - 22	5064	65770	34.20
Florida Stratum 3 - 23	5073	69349	3.10
Florida Stratum 3 - 24	5073	98336	1,898.10
Florida Stratum 3 - 25	5047	67662	26.00
Florida Stratum 3 - 26	5073	60421	300.30
Florida Stratum 3 - 27	5064	99260	306.90
Florida Stratum 3 - 28	5073	98364	186.00
Florida Stratum 3 - 29	5073	98809	103.90
Florida Stratum 3 - 30	5064	98265	1,128.80
Florida Stratum 3 - 31	5064	98906	357.10
Florida Stratum 3 - 32	5073	98611	590.70
Florida Stratum 3 - 33	5073	60700	740.70
Florida Stratum 3 - 34	5073	98474	157.80
Florida Stratum 3 - 35	5073	98492	17.60

ATTACHMENT 6B

Upcharges Among Randomly Selected Combinations of Cost Center and Machine Number in South Carolina

Random Order Within Stratum	Cost Center	Machine Number	Upcharges
Within South Carolina Stratum 1 - Upcharges in South Carolina are calculated through the day prior to the earliest survey date			
South Carolina Stratum 1 - 1	5902	66693	$ 46.01
South Carolina Stratum 1 - 2	5273	65198	447.26
South Carolina Stratum 1 - 3	5539	94758	15.36
South Carolina Stratum 1 - 4	5273	65399	138.69
South Carolina Stratum 1 - 5	5539	67161	23.38
South Carolina Stratum 1 - 6	5902	97374	228.73
South Carolina Stratum 1 - 7	5273	66962	123.44
South Carolina Stratum 1 - 8	5539	93072	1.03
South Carolina Stratum 1 - 9	5539	94634	0.05
South Carolina Stratum 1 - 10	5273	93591	238.00
South Carolina Stratum 1 - 11	5273	65104	794.12
South Carolina Stratum 1 - 12	5902	66200	1,320.90
South Carolina Stratum 1 - 13	5273	67003	89.90
South Carolina Stratum 1 - 14	5539	67368	117.83
South Carolina Stratum 1 - 15	5902	66855	194.22
South Carolina Stratum 1 - 16	5539	92159	27.65
South Carolina Stratum 1 - 17	5273	68197	39.94
South Carolina Stratum 1 - 18	5539	67331	20.23
South Carolina Stratum 1 - 19	5539	94641	0.68
South Carolina Stratum 1 - 20	5902	98234	20.99
South Carolina Stratum 1 - 21	5539	94024	11.94
South Carolina Stratum 1 - 22	5902	92264	206.92
South Carolina Stratum 1 - 23	5273	96675	555.00
South Carolina Stratum 1 - 24	5539	67226	61.58
South Carolina Stratum 1 - 25	5539	92144	0.30
South Carolina Stratum 1 - 26	5539	94520	20.23
South Carolina Stratum 1 - 27	5273	96346	36.73
South Carolina Stratum 1 - 28	5539	67719	1.47
South Carolina Stratum 1 - 29	5273	96408	231.10
South Carolina Stratum 1 - 30	5902	97131	10.86
South Carolina Stratum 1 - 31	5273	66325	1,524.54
South Carolina Stratum 1 - 32	5273	96389	102.05
South Carolina Stratum 1 - 33	5539	94308	94.15
South Carolina Stratum 1 - 34	5273	66396	219.90
South Carolina Stratum 1 - 35	5273	95535	136.02
South Carolina Stratum 1 - 36	5539	67355	85.08
South Carolina Stratum 1 - 37	5273	66921	305.20
South Carolina Stratum 1 - 38	5273	95727	525.24
South Carolina Stratum 1 - 39	5902	95211	114.26
South Carolina Stratum 1 - 40	5902	69122	828.19
South Carolina Stratum 1 - 41	5902	97713	85.58

Upcharges Among Randomly Selected Combinations of Cost Center and Machine Number in South Carolina

Random Order Within Stratum	Cost Center	Machine Number	Upcharges
South Carolina Stratum 1 - 42	5902	98093	183.80
South Carolina Stratum 1 - 43	5902	90138	25.30
South Carolina Stratum 1 - 44	5902	66610	154.88
South Carolina Stratum 1 - 45	5273	68305	537.66
South Carolina Stratum 1 - 46	5902	98173	74.66
South Carolina Stratum 1 - 47	5273	94471	158.16
South Carolina Stratum 1 - 48	5902	97354	438.60
South Carolina Stratum 1 - 49	5539	92871	0.64
South Carolina Stratum 1 - 50	5902	72507	256.57
South Carolina Stratum 1 - 51	5539	67558	0.46
South Carolina Stratum 1 - 52	5539	67393	0.18
South Carolina Stratum 1 - 53	5539	67723	74.51
South Carolina Stratum 1 - 54	5539	67447	1.60
South Carolina Stratum 1 - 55	5273	66797	202.98
South Carolina Stratum 1 - 56	5273	65339	134.19
South Carolina Stratum 1 - 57	5902	98203	41.56
South Carolina Stratum 1 - 58	5902	97510	268.31
South Carolina Stratum 1 - 59	5902	92374	602.70
South Carolina Stratum 1 - 60	5539	92555	118.10
South Carolina Stratum 1 - 61	5902	97706	835.65
South Carolina Stratum 1 - 62	5539	67749	415.57
South Carolina Stratum 1 - 63	5902	69338	118.80
South Carolina Stratum 1 - 64	5539	67237	94.52
South Carolina Stratum 1 - 65	5273	65219	587.77
Within South Carolina Stratum 3 - Upcharges in South Carolina are calculated through the end of the Two-Tier Revenue Report			
South Carolina Stratum 3 - 1	5273	68585	$ 72.70
South Carolina Stratum 3 - 2	5273	68052	745.80
South Carolina Stratum 3 - 3	5273	72537	42.00
South Carolina Stratum 3 - 4	5273	96261	106.60
South Carolina Stratum 3 - 5	5273	21733	20.20
South Carolina Stratum 3 - 6	5273	96969	69.90
South Carolina Stratum 3 - 7	5273	96943	265.20
South Carolina Stratum 3 - 8	5273	95340	246.80
South Carolina Stratum 3 - 9	5141	99863	163.70
South Carolina Stratum 3 - 10	5273	96945	53.80
South Carolina Stratum 3 - 11	5273	68625	70.30
South Carolina Stratum 3 - 12	5273	97011	3.60
South Carolina Stratum 3 - 13	5273	68583	55.40
South Carolina Stratum 3 - 14	5273	66920	908.20
South Carolina Stratum 3 - 15	5141	64745	134.60
South Carolina Stratum 3 - 16	5141	97732	1,438.80

Upcharges Among Randomly Selected Combinations of Cost Center and Machine Number in South Carolina

Random Order Within Stratum	Cost Center	Machine Number	Upcharges
South Carolina Stratum 3 - 17	5273	66316	532.20
South Carolina Stratum 3 - 18	5273	66787	354.20
South Carolina Stratum 3 - 19	5273	68070	78.70
South Carolina Stratum 3 - 20	5273	96985	121.30
South Carolina Stratum 3 - 21	5273	66487	192.90
South Carolina Stratum 3 - 22	5273	96908	83.60
South Carolina Stratum 3 - 23	5273	96993	27.30
South Carolina Stratum 3 - 24	5141	98890	47.90
South Carolina Stratum 3 - 25	5273	68603	247.80
South Carolina Stratum 3 - 26	5273	65261	241.40
South Carolina Stratum 3 - 27	5273	66725	445.40
South Carolina Stratum 3 - 28	5273	65063	330.20
South Carolina Stratum 3 - 29	5273	68630	55.80
South Carolina Stratum 3 - 30	5539	92659	2.90
South Carolina Stratum 3 - 31	5273	96988	287.50
South Carolina Stratum 3 - 32	5539	94680	1.40
South Carolina Stratum 3 - 33	5273	65666	461.70
South Carolina Stratum 3 - 34	5273	96974	203.10
South Carolina Stratum 3 - 35	5273	68627	29.50

ATTACHMENT 7A

Potential Pre-Judgment Interest Among Randomly Selected Combinations of Cost Center and Machine Number in Florida

Random Order Within Stratum	Cost Center	Machine Number	Pre-Judgment Interest Through 3/7/2024
Within Florida Stratum 1 - Interest is based on Upcharges in Florida through the day prior to the earliest survey date			
Florida Stratum 1 - 1	5080	66801	$ 0.70
Florida Stratum 1 - 2	5080	66461	11.91
Florida Stratum 1 - 3	5047	66019	318.16
Florida Stratum 1 - 4	5073	66149	36.38
Florida Stratum 1 - 5	5073	97343	7.94
Florida Stratum 1 - 6	5073	97392	3.04
Florida Stratum 1 - 7	5064	96366	105.27
Florida Stratum 1 - 8	5564	94030	1.08
Florida Stratum 1 - 9	5064	65184	110.22
Florida Stratum 1 - 10	5564	94362	5.99
Florida Stratum 1 - 11	5047	66807	466.06
Florida Stratum 1 - 12	5073	68976	96.13
Florida Stratum 1 - 13	5073	98055	10.27
Florida Stratum 1 - 14	5064	63824	623.01
Florida Stratum 1 - 15	5073	97130	44.15
Florida Stratum 1 - 16	5064	61425	49.88
Florida Stratum 1 - 17	5047	94251	4.84
Florida Stratum 1 - 18	5544	93029	56.08
Florida Stratum 1 - 19	5080	66580	1,095.17
Florida Stratum 1 - 20	5545	90829	8.75
Florida Stratum 1 - 21	5073	90339	76.79
Florida Stratum 1 - 22	5047	94186	284.57
Florida Stratum 1 - 23	5545	72274	31.96
Florida Stratum 1 - 24	5064	97430	31.58
Florida Stratum 1 - 25	5080	93604	56.55
Florida Stratum 1 - 26	5085	60475	243.47
Florida Stratum 1 - 27	5073	67654	52.79
Florida Stratum 1 - 28	5085	61224	39.14
Florida Stratum 1 - 29	5047	94941	28.85
Florida Stratum 1 - 30	5545	95564	75.65
Florida Stratum 1 - 31	5564	94181	2.52
Florida Stratum 1 - 32	5564	94485	31.61
Florida Stratum 1 - 33	5064	60537	185.36
Florida Stratum 1 - 34	5564	66225	1.61
Florida Stratum 1 - 35	5085	97014	64.63
Florida Stratum 1 - 36	5545	98038	335.24
Florida Stratum 1 - 37	5047	66301	34.64
Florida Stratum 1 - 38	5073	96540	6.85
Florida Stratum 1 - 39	5064	97877	13.70

Potential Pre-Judgment Interest Among Randomly Selected Combinations of Cost Center and Machine Number in Florida

Random Order Within Stratum	Cost Center	Machine Number	Pre-Judgment Interest Through 3/7/2024
Florida Stratum 1 - 40	5064	63139	1,385.64
Florida Stratum 1 - 41	5073	67424	158.55
Florida Stratum 1 - 42	5085	97040	50.34
Florida Stratum 1 - 43	5080	61081	72.38
Florida Stratum 1 - 44	5064	63603	125.29
Florida Stratum 1 - 45	5073	91401	588.45
Florida Stratum 1 - 46	5073	97869	44.84
Florida Stratum 1 - 47	5047	66124	91.42
Florida Stratum 1 - 48	5544	60064	6.72
Florida Stratum 1 - 49	5545	97931	36.84
Florida Stratum 1 - 50	5545	97578	82.48
Florida Stratum 1 - 51	5080	94984	0.73
Florida Stratum 1 - 52	5064	90508	551.98
Florida Stratum 1 - 53	5064	65217	146.90
Florida Stratum 1 - 54	5064	92852	103.86
Florida Stratum 1 - 55	5064	90213	22.86
Florida Stratum 1 - 56	5545	64277	127.51
Florida Stratum 1 - 57	5545	97618	266.39
Florida Stratum 1 - 58	5085	60123	148.02
Florida Stratum 1 - 59	5047	66207	130.89
Florida Stratum 1 - 60	5085	61216	59.53
Florida Stratum 1 - 61	5064	69075	4.74
Florida Stratum 1 - 62	5064	94502	92.68
Florida Stratum 1 - 63	5064	63311	121.41
Florida Stratum 1 - 64	5544	90395	163.12
Florida Stratum 1 - 65	5073	96725	25.06
Within Florida Stratum 1 - Interest is based on Upcharges in Florida through March 2023			
Florida Stratum 3 - 1	5073	60364	$ 106.41
Florida Stratum 3 - 2	5545	66777	14.80
Florida Stratum 3 - 3	5047	95110	14.06
Florida Stratum 3 - 4	5073	98381	39.70
Florida Stratum 3 - 5	5073	60585	26.34
Florida Stratum 3 - 6	5064	98957	4.47
Florida Stratum 3 - 7	5073	60488	3.74
Florida Stratum 3 - 8	5073	60282	51.22
Florida Stratum 3 - 9	5080	94931	11.08
Florida Stratum 3 - 10	5073	60662	66.22
Florida Stratum 3 - 11	5564	66496	39.39
Florida Stratum 3 - 12	5073	60460	7.46

Potential Pre-Judgment Interest Among Randomly Selected Combinations of Cost Center and Machine Number in Florida

Random Order Within Stratum	Cost Center	Machine Number	Pre-Judgment Interest Through 3/7/2024
Florida Stratum 3 - 13	5545	60655	96.12
Florida Stratum 3 - 14	5545	61479	12.66
Florida Stratum 3 - 15	5085	26039	0.09
Florida Stratum 3 - 16	5073	98706	13.21
Florida Stratum 3 - 17	5064	98739	30.30
Florida Stratum 3 - 18	5085	99402	146.55
Florida Stratum 3 - 19	5564	66504	60.94
Florida Stratum 3 - 20	5545	90060	1.38
Florida Stratum 3 - 21	5073	97634	129.58
Florida Stratum 3 - 22	5064	65770	1.98
Florida Stratum 3 - 23	5073	69349	0.23
Florida Stratum 3 - 24	5073	98336	225.84
Florida Stratum 3 - 25	5047	67662	1.34
Florida Stratum 3 - 26	5073	60421	28.02
Florida Stratum 3 - 27	5064	99260	21.29
Florida Stratum 3 - 28	5073	98364	15.67
Florida Stratum 3 - 29	5073	98809	7.76
Florida Stratum 3 - 30	5064	98265	96.79
Florida Stratum 3 - 31	5064	98906	33.42
Florida Stratum 3 - 32	5073	98611	60.37
Florida Stratum 3 - 33	5073	60700	67.33
Florida Stratum 3 - 34	5073	98474	15.39
Florida Stratum 3 - 35	5073	98492	1.88

ATTACHMENT 7B

Potential Pre-Judgment Interest Among Randomly Selected Combinations of Cost Center and Machine Number in South Carolina

Random Order Within Stratum	Cost Center	Machine Number	Pre-Judgment Interest Through 3/7/2024
Within South Carolina Stratum 1 - Interest is based on Upcharges in South Carolina through the day prior to the earliest survey date			
South Carolina Stratum 1 - 1	5902	66693	$ 21.42
South Carolina Stratum 1 - 2	5273	65198	212.94
South Carolina Stratum 1 - 3	5539	94758	7.43
South Carolina Stratum 1 - 4	5273	65399	75.83
South Carolina Stratum 1 - 5	5539	67161	12.07
South Carolina Stratum 1 - 6	5902	97374	116.47
South Carolina Stratum 1 - 7	5273	66962	65.25
South Carolina Stratum 1 - 8	5539	93072	0.38
South Carolina Stratum 1 - 9	5539	94634	0.00
South Carolina Stratum 1 - 10	5273	93591	130.50
South Carolina Stratum 1 - 11	5273	65104	477.29
South Carolina Stratum 1 - 12	5902	66200	763.90
South Carolina Stratum 1 - 13	5273	67003	43.53
South Carolina Stratum 1 - 14	5539	67368	57.62
South Carolina Stratum 1 - 15	5902	66855	89.94
South Carolina Stratum 1 - 16	5539	92159	13.10
South Carolina Stratum 1 - 17	5273	68197	17.88
South Carolina Stratum 1 - 18	5539	67331	9.01
South Carolina Stratum 1 - 19	5539	94641	0.18
South Carolina Stratum 1 - 20	5902	98234	8.83
South Carolina Stratum 1 - 21	5539	94024	5.50
South Carolina Stratum 1 - 22	5902	92264	111.05
South Carolina Stratum 1 - 23	5273	96675	252.72
South Carolina Stratum 1 - 24	5539	67226	31.12
South Carolina Stratum 1 - 25	5539	92144	0.08
South Carolina Stratum 1 - 26	5539	94520	9.66
South Carolina Stratum 1 - 27	5273	96346	17.41
South Carolina Stratum 1 - 28	5539	67719	0.53
South Carolina Stratum 1 - 29	5273	96408	122.50
South Carolina Stratum 1 - 30	5902	97131	4.77
South Carolina Stratum 1 - 31	5273	66325	801.14
South Carolina Stratum 1 - 32	5273	96389	48.15
South Carolina Stratum 1 - 33	5539	94308	45.22
South Carolina Stratum 1 - 34	5273	66396	125.61
South Carolina Stratum 1 - 35	5273	95535	86.89
South Carolina Stratum 1 - 36	5539	67355	40.29
South Carolina Stratum 1 - 37	5273	66921	148.15
South Carolina Stratum 1 - 38	5273	95727	279.16
South Carolina Stratum 1 - 39	5902	95211	60.75
South Carolina Stratum 1 - 40	5902	69122	557.04
South Carolina Stratum 1 - 41	5902	97713	41.05

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Random Order Within Stratum	Cost Center	Machine Number	Pre-Judgment Interest Through 3/7/2024
South Carolina Stratum 1 - 42	5902	98093	87.17
South Carolina Stratum 1 - 43	5902	90138	10.64
South Carolina Stratum 1 - 44	5902	66610	76.88
South Carolina Stratum 1 - 45	5273	68305	255.64
South Carolina Stratum 1 - 46	5902	98173	35.08
South Carolina Stratum 1 - 47	5273	94471	77.83
South Carolina Stratum 1 - 48	5902	97354	204.52
South Carolina Stratum 1 - 49	5539	92871	0.18
South Carolina Stratum 1 - 50	5902	72507	135.12
South Carolina Stratum 1 - 51	5539	67558	0.19
South Carolina Stratum 1 - 52	5539	67393	0.05
South Carolina Stratum 1 - 53	5539	67723	21.41
South Carolina Stratum 1 - 54	5539	67447	0.82
South Carolina Stratum 1 - 55	5273	66797	120.98
South Carolina Stratum 1 - 56	5273	65339	65.21
South Carolina Stratum 1 - 57	5902	98203	18.72
South Carolina Stratum 1 - 58	5902	97510	149.07
South Carolina Stratum 1 - 59	5902	92374	368.96
South Carolina Stratum 1 - 60	5539	92555	58.58
South Carolina Stratum 1 - 61	5902	97706	394.01
South Carolina Stratum 1 - 62	5539	67749	212.50
South Carolina Stratum 1 - 63	5902	69338	59.12
South Carolina Stratum 1 - 64	5539	67237	53.77
South Carolina Stratum 1 - 65	5273	65219	339.51
Within South Carolina Stratum 1 - Interest is based on Upcharges in South Carolina through March 2023			
South Carolina Stratum 3 - 1	5273	68585	$ 9.25
South Carolina Stratum 3 - 2	5273	68052	409.95
South Carolina Stratum 3 - 3	5273	72537	4.38
South Carolina Stratum 3 - 4	5273	96261	37.43
South Carolina Stratum 3 - 5	5273	21733	11.46
South Carolina Stratum 3 - 6	5273	96969	10.68
South Carolina Stratum 3 - 7	5273	96943	40.17
South Carolina Stratum 3 - 8	5273	95340	85.69
South Carolina Stratum 3 - 9	5141	99863	13.58
South Carolina Stratum 3 - 10	5273	96945	8.01
South Carolina Stratum 3 - 11	5273	68625	6.96
South Carolina Stratum 3 - 12	5273	97011	0.47
South Carolina Stratum 3 - 13	5273	68583	7.69
South Carolina Stratum 3 - 14	5273	66920	464.03
South Carolina Stratum 3 - 15	5141	64745	11.23
South Carolina Stratum 3 - 16	5141	97732	218.23

Potential Pre-Judgment Interest Among Randomly Selected Combinations of Cost Center and Machine Number in South Carolina

Random Order Within Stratum	Cost Center	Machine Number	Pre-Judgment Interest Through 3/7/2024
South Carolina Stratum 3 - 17	5273	66316	132.07
South Carolina Stratum 3 - 18	5273	66787	59.85
South Carolina Stratum 3 - 19	5273	68070	32.14
South Carolina Stratum 3 - 20	5273	96985	13.91
South Carolina Stratum 3 - 21	5273	66487	60.03
South Carolina Stratum 3 - 22	5273	96908	19.49
South Carolina Stratum 3 - 23	5273	96993	3.51
South Carolina Stratum 3 - 24	5141	98890	6.08
South Carolina Stratum 3 - 25	5273	68603	25.65
South Carolina Stratum 3 - 26	5273	65261	100.85
South Carolina Stratum 3 - 27	5273	66725	82.97
South Carolina Stratum 3 - 28	5273	65063	63.95
South Carolina Stratum 3 - 29	5273	68630	5.25
South Carolina Stratum 3 - 30	5539	92659	0.42
South Carolina Stratum 3 - 31	5273	96988	34.16
South Carolina Stratum 3 - 32	5539	94680	0.11
South Carolina Stratum 3 - 33	5273	65666	162.81
South Carolina Stratum 3 - 34	5273	96974	28.80
South Carolina Stratum 3 - 35	5273	68627	2.91